Machine Learning for Neural Decoding: Using EEG Signals to Detect Freezing of Gait in Parkinson's Patients

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Abstract—**Freezing of gait (FOG) is one of the most serious and poorly understood symptoms of Parkinson's Disease (PD). The main focus of this paper is to examine correlations between electroencephalography (EEG) data and episodes of FOG. Ultimately, the goal of the project is the development of a machine-learning model capable of detecting instances of FOG in Parkinson's patients. EEG data was retrieved from an existing dataset, processed, and analyzed using linear regressions to evaluate relationships between the variables. Then, the data was run through four predictive models: a polynomial regression, a dense neural network, a Bayesian neural network, and an autoencoder. The dense neural network generated the best results for multi-patient data with an accuracy rate of 66%. However, when the Dense neural network analyzed data from an individual patient engaged in one task, its accuracy increased sharply to 80-94%. One potential application of this research would be the development of personal EEG tracking and Parkinson's symptom prediction systems.**

I. INTRODUCTION

Parkinson's Disease (PD) is a common progressive brain disease that affects movement. Approximately 10 million people suffer from PD worldwide [1]. Degeneration occurs in the dopamine-producing neurons located in the substantia nigra. Dopamine plays a crucial role in regulating and recalling coordinated movement and as the disease progresses and more dopamine-producing neurons deteriorate, motor symptoms arise.

Freezing of gait (FOG) is a disabling symptom of PD characterized by the inability to initiate motion while attempting to walk, often resulting in potentially harmful falls [2]. FOG is associated with a loss of freedom and a decrease in quality of life.

A link between EEG data and FOG would contribute to the very limited understanding of FOG, allowing scientists and medical professionals to better understand and thus help treat the debilitating symptom and possibly the overall disease to some extent. Furthermore, assessing FOG is currenlty a difficult process requiring intense movement analysis, but by discovering a relationship, EEG data could be used as a biomarker for FOG. This is especially notable due to the accessible nature of collecting EEG signals. Finally, a connection between the two would allow for the creation of closed-loop FOG prediction systems. These systems may be able to detect an anomaly in EEG signals and warn the Parkinson's patient in advance of a FOG episode, thus reducing potential harm inflicted by FOG on Parkinson's patients.

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II. BACKGROUND

A. Freezing of Gait

FOG and its causes are not fully understood [3]. Scientists speculate that deficiencies in the basal ganglia are linked to FOG episodes [4]. In normal function of the brain, inhibition of the striatum results in inhibition of the globus pallidus pars externus (GPe), in turn inhibiting the globus pallidus/substantia nigra pars reticulata (GPi/SNr) pathway and executing learned tasks. However, it is theorized that in patients with PD, a deficiency in dopamine due to the impairment or death of nerve cells in the basal ganglia [4] causes a lack of proper inhibition of the GPi/SNr pathway, resulting in decreased gait control. A secondary theory in the causation of FOG episodes is a disorder of neural circuitry. Should a network perturbation occur, connectivity between neurons and information processing within the brain may be negatively impacted, thus causing freezing of gait [2]. Studies have also suggested that a reduced frequency of FOG occurrences is associated with the reduction of visual cues, audio cues, and intensity of emotion in patients [2]. This indicates that attention is a significant factor in the causation of FOG, implicating the frontal lobe.

B. Bayesian Neural Networks (BNNs) and Autoencoders

BNNs are distinct from standard neural networks due to their weights being probabilistic distributions [5]. Furthermore, Autoencoders are distinct from standard neural networks because they size down their input, store it in latent space, and size it back up allowing for feature extraction [6].

III. EXPERIMENTAL PROCEDURE

A. Data Sourcing and Processing

The dataset for this project is taken from a 2022 study “Multimodal Data for the Detection of Freezing of Gait in Parkinson’s Disease” by Zhang et. al. [7] in which researchers conducted experiments designed to cause FOG episodes. Each patient completed 4 walking tasks (tasks 1 and 2 and tasks 3 and 4 were identical). The dataset contains 12 patients and 13 completed experiments (Patient ID:08 completed two experiments on separate dates). 3 Hours and 42 minutes of valid EEG data was obtained using a 32-channel wireless MOVE system (MOVE, Brain Products GmbH, Gilching, Germany).

Preprocessed and filtered data from “Multimodal Data” was used and sorted to remove non-neural data. The final structure of data used was 500 Hz and made up of 26 columns; the first 25 refer to EEG channels and the last contains boolean information indicating the occurrence of FOG.

Data was then sorted into different CSV files so that varying experiments could be conducted. Firstly, data from all patients and tasks were combined so that studies could be performed on all available data. Because of limitations in computational power, data in this file was reduced by a factor of 99%, keeping one data point from every 0.2 seconds (to 5 Hz). This downsampling to a lower frequency of 5 Hz causes a decrease in the maximum frequency of the signal to 2.5 H due to the Nyquist-Shannon Sampling Theorem. Another two files were created which each contained a type of task participants in the original dataset conducted. Tasks 1 and 2 were combined, as were tasks 3 and 4. Data in these files were also reduced to 5 Hz. Single patient single task type data (which refers for instance to Patient ID:001 Task 1 or Patient ID:009 Task 3) was not downscaled and remained at 500 Hz. Only data of this type was not downscaled.

B. Linear Regression

For linear regressions, data was processed with a moving average of 1000 data points (2 seconds) after the incidence of FOG. Simple one-variable regressions were used to first identify the correlation between each of the 25 EEG signals and FOG, and then multivariate regressions were employed to examine the effectiveness of predicting FOG using multiple EEG channel signals.

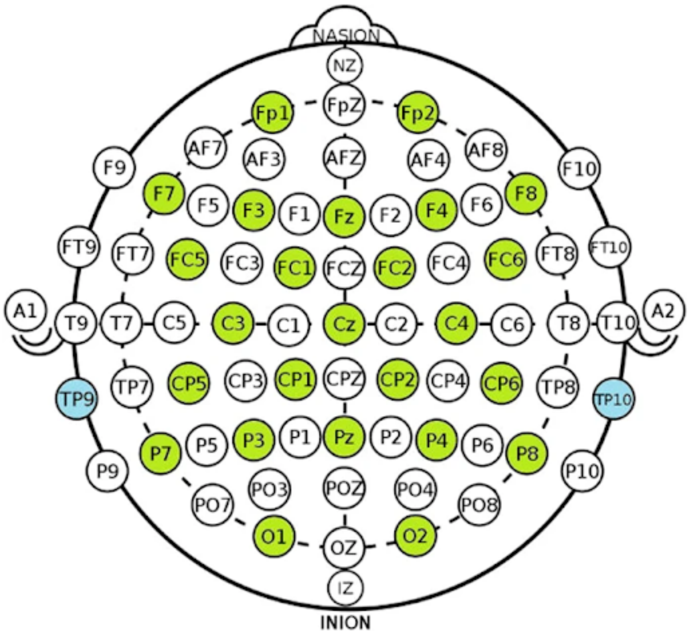


Fig. 1. Depiction of the electrode set up of the experiments; green electrodes represent EEG channels recorded in the study. [7]

C. Polynomial Regression

Polynomial regression was performed via a machine learning model which looked for polynomial-based relationships within EEG data and made predictions on the patient’s FOG status. The performance of polynomial regression was evaluated as a final percent accuracy in the model’s guesses.

D. Dense Neural Network

A Keras densely connected neural network was created to examine potential correlations between EEG signals and occurrences of FOG. The model used had 5 total layers which consisted of an input, 3 hidden, and 1 output layer. To optimize this model, various layers were added and tested. Batch normalization was implemented, and the model’s learning rate was adjusted. The learning rate used was 0.001, determined by testing a range of different rates and using the one with the best accuracy.

The Keras DNN was initially trained and tested using data from a variety of different patients and tasks. However, due to low accuracy using multi patient data, likely from the vast differences in people’s brains, it was decided that the model would be trained on patient by patient and task by task data, implementing a “personalized medicine” model. Following this, the model was trained and tested 12 times. This included Patient IDs: 3, 7, 8.2, 9, 10, and 11 performing both task 1/2 and task 3/4.

E. Bayesian Neural Network

This model utilized TensorFlow and TensorFlow Probability (TFP) to perform binary classification, sorting the data into two classes.

The EEG dataset was split into training and testing data. The target variable (train_y), consisted of the status column, which represented whether or not the patient was in an episode of FOG as a boolean value. The input feature (train_x) was isolated by removing the status column from the training data.

The BNN model was defined using Keras Sequential API. The model consists of a 25-node input layer and three hidden layers, which were implemented using TFP's DenseFlipout. DenseFlipout layers apply dropout during training to model uncertainty in the weight distributions, capturing epistemic uncertainty. The activation function used for the hidden layers introduces non-linearity to the model.

The model was compiled using an optimizer and a loss function, with an evaluation metric for accuracy. The model was trained using train_x and train_y, in sets of 128 for 50 epochs. The model adjusted its weights during training to minimize binary cross-entropy loss and improve its performance on training data.

F. Autoencoder

An autoencoder was implemented using PyTorch to predict the status of single patients based on input data from 16 channels indicating the occurrence of FOG. The data was standardized to have zero mean and unit variance, then split into training and testing datasets. The data was then converted into PyTorch tensors to be used in the model.

The autoencoder was initialized with hyperparameters such as input dimension (number of channels), encoding dimension (dimensionality of the compressed representation), learning rate, and the number of epochs for training. A Mean Squared Error (MSE) loss function and Adam optimizer with L2 regularization were set up for training.

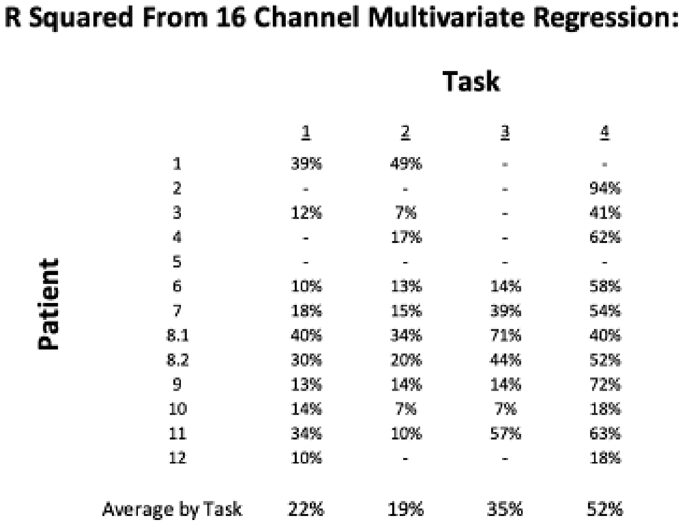
The model was trained on the training dataset in a loop over the specified number of epochs. In each epoch, the autoencoder was set to training mode, and the optimizer's gradients were set to zero. The data was passed forward through the autoencoder, and the loss was calculated as the MSE between the original input and the reconstructed output. The gradients were then back-propagated through the network, and the optimizer updated the model's parameters. A learning rate scheduler was implemented at the end of each epoch to reduce the learning rate and enhance it. convergence.

After training, the autoencoder was evaluated on the test dataset to compute the test loss using the same MSE function. The trained autoencoder was then used for classification. The data was encoded, and a threshold of 0.5 was applied to the mean of the encoded data to make binary predictions about the FOG status of patients, where a value greater than 0.5 indicates a positive status prediction. The predicted binary values were converted into floating point numbers (0.0 or 1.0), and the accuracy was calculated by comparing the predictions to the labels from the test set.

IV. RESULTS AND DISCUSSION

A. Linear Regression

The results of the multiple regression analysis for each task using the 16 EEG signal variables with the highest R-Squared results (out of the 25 single variable regressions done for that task) as the independent variables are shown in Figure 2. R-Squared values varied greatly by patient and by task.



R Squared From 16 Channel Multivariate Regression:

Patient	Task 1	Task 2	Task 3	Task 4
1	39%	49%	-	-
2	-	-	-	94%
3	12%	7%	-	41%
4	-	17%	-	62%
5	-	-	-	-
6	10%	13%	14%	58%
7	18%	15%	39%	54%
8.1	40%	34%	71%	40%
8.2	30%	20%	44%	52%
9	13%	14%	14%	72%
10	14%	7%	7%	18%
11	34%	10%	57%	63%
12	10%	-	-	18%
Average by Task	22%	19%	35%	52%

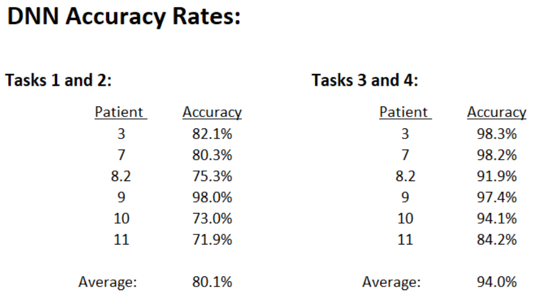
Fig. 2. Linear Regression Result Table; Blank spaces indicate either an absence of available data for that patient and task combination or an experiment in which no episodes of FOG occurred.

B. Polynomial Regression

On average, the polynomial regression was 60.3% accurate at predicting FOG for single patient single task data (ex: Patient ID:001 Task 1). This average shows the effectiveness of polynomial regressions in finding complex relationships between data.

Polynomial regressions conducted on entire tasks shared a similar accuracy rate. On multi-patient data for tasks 1 and 2, the polynomial regression achieved an accuracy rate of 61.1%. On multi-patient data for tasks 3 and 4, the accuracy rate was similar at 64.6%.

C. Dense Neural Network



DNN Accuracy Rates:

Tasks 1 and 2:

Patient	Accuracy
3	82.1%
7	80.3%
8.2	75.3%
9	98.0%
10	73.0%
11	71.9%
Average:	80.1%

Tasks 3 and 4:

Patient	Accuracy
3	98.3%
7	98.2%
8.2	91.9%
9	97.4%
10	94.1%
11	84.2%
Average:	94.0%

Fig. 3. Table showing results of DNN.

The data displayed in figure 3 suggests that for a single task on a single patient, the DNN model is highly accurate at predicting whether or not FOG is occurring. It also strongly supports the idea that EEG is a biomarker for FOG.

While the DNN model is highly accurate at single-patient datasets, it is not as accurate at multi-patient. When using a multi-patient dataset the accuracy was 66%. This indicates that while the model is able to make substantially accurate predictions of FOG, more research is required for utilization in clinical applications. However, this lower accuracy may be explained by the use of downsized datasets for multi-patient data. It is possible that if the model were run on 500 Hz multi-patient datasets, its accuracy would improve.

D. Bayesian Neural Network

The data suggests that for a single task, the model is not sufficiently efficient at predicting the occurrence of FOG as we received an accuracy of around 55.6%. This is most likely due to the weights in a BNN being a probabilistic distribution compared to a normal neural network having a set value for them. Due to having the weights be a range rather than a set value, more CPU load is present, meaning more time is taken for the calculations. For that reason, it was necessary to use a smaller number of epochs which also could have contributed to the lower accuracy.

E. Autoencoder

The accuracy for the single-patient data was 63%, significantly lower than the DNN. This decrease is due to the very nature of the autoencoder itself. To begin, autoencoders typically have a bottleneck layer hidden in the encoding process. This layer forces the network to learn a compressed version of all input data, reducing the overall output. This compressing layer can be extremely beneficial for the network, as certain features from the input data can be extracted and only the most important information will be retained by the output. However, the bottleneck can serve as both an advantage and disadvantage based on the capacity of the layer. Bottleneck layers are always limited in capacity, which can be problematic for complex forms of data. The autoencoder likely omitted a considerable amount of important EEG data when processed in the bottleneck layer and decreased the accuracy of the model.

V. CONCLUSION

This project has analyzed correlations between EEG data and FOG episodes using multiple methods. The DNN model shows promising results when data is limited to individual patients and tasks (i.e. 80% and 94% accuracy averages for single patient tasks 1/2 and 3/4 respectively). This implies potential usefulness for EEG data in treatment of FOG symptoms.

The highest degree of accuracy for multi-patient data was also achieved by using the DNN neural network. A 66% accuracy in prediction across patients indicates that there is some universal correlation between EEG data and episodes of FOG. However, while this level of accuracy indicates predictive power over simple guessing, multi-patient DNN-based FOG prediction would require further improvement to have clinical viability.

Challenges to overcome in the future will include developing a larger set of usable data, processing the data to eliminate EEG signal noise and finding the optimal procedure to model nonlinear relationships in the data.

A. Future Improvements

One concern for this study was the inadequate quantity of data used, which only consisted of 12 patients and about 3 hours and 42 minutes of EEG signals. This sample is relatively small and is bound to be adversely affected by outliers. By using a larger dataset, the risk of skewing the accuracy will be minimized. Additionally, EEG data by itself tends to contain a significant amount of noise due to the channels collecting irrelevant data from the scalp area. Therefore, multiple types of intracranial data should be used to better represent the neural activity of the patients and provide more definite results.

In addition, the authors lacked the computing power necessary to run the neural network with the complete set of data. The neural networks only had the capacity to use approximately 1/100 of all available data for multi-patient analyses. With a more powerful computer, the neural network would have been able to use the entire dataset and likely reach a more accurate conclusion. Also, the models in this study were only run to evaluate relationships in the data and were not used to predict future episodes of FOG.

B. Future Applications

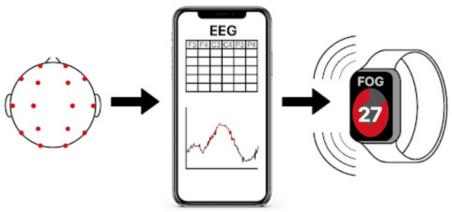


Fig. 4. Depiction of EEG tracking system.

This research has a vast array of potential applications. If further study is able to expand upon these findings and is successful in predicting future FOG events, a real-time implementation of this research could be in the form of an application and wearable apparatus containing an EEG tracking device transmitting signals to an iOS/android-based application using a neural network to predict a potential occurrence of FOG in the next 30 seconds. If there is a potential occurrence, the application will alert the user and instruct them to stop what they are doing. The alert will help them prepare, which would make FOG much less dangerous by allowing the patient to sit down or find a less dangerous place to be in.

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VI. APPENDIX

In this section are the links to the code used for: the polynomial regression, DNN neural network, the BNN, and the autoencoder.

https://www.kaggle.com/code/kjohnson0/polynomial-regressions
https://www.kaggle.com/code/ranajoygupta/dense-nn
https://www.kaggle.com/code/ritviksawhney/bayesian-nn
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