

INTRO

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects millions of people worldwide. The disease primarily impacts the dopaminergic neurons in the substantia nigra, leading to motor symptoms such as tremors, muscle rigidity, and loss of balance. Early diagnosis of PD is crucial for better management of the disease, allowing for early initiation of treatment and improved patient outcomes.

Currently, there is no definitive test for PD; diagnosis relies primarily on the evaluation of clinical symptoms, which often appear several years after the onset of the disease. This delayed detection limits the potential for early intervention and disease management. As a result, there is a growing need for non-invasive, cost-effective, and reliable methods to detect PD at an early stage.

In this study, I propose a novel approach for early PD detection by capturing respiratory breathing patterns during sleep using smartphone-generated ultrasonic rays. I employ a Deep Neural Network (DNN) model combining a convolutional neural network (CNN) and a recurrent neural network (RNN) for the classification of the breathing signals into two classes: PD and control.

MATERIALS AND METHODS

Data Collection:

We collected data from a single source, a publicly available dataset containing the respiratory breathing patterns of individuals with PD and age-matched control subjects during sleep. The dataset consisted of two-dimensional signals representing the respiratory patterns of the subjects. Each signal in the dataset was labeled either as PD or control, allowing for supervised learning. The dataset was randomly split into training (80%) and testing (20%) sets, ensuring a fair evaluation of the model's performance.

Software and Hardware:

We used a Jupyter Notebook running on a standard computer with a GPU for training the machine learning model. Python programming language was used for data preprocessing, model development, and evaluation. The deep learning model was implemented using the TensorFlow framework, an open-source library for machine learning and artificial intelligence.

Data Preprocessing:

The raw data was preprocessed to ensure compatibility with the deep learning model. First, the data was normalized to account for potential variations in the amplitude of the breathing signals. Next, the signals were segmented into fixed-length windows to create a uniform input size for the CNN. These windows were chosen based on the average length of the respiratory cycles, ensuring that the model would capture relevant features from the breathing patterns.

Model Development:

The deep learning model consists of a CNN to extract features from the input breathing signals, followed by a dropout layer to prevent overfitting. The output from the CNN is fed into a Long Short-Term Memory (LSTM) layer with 16 units, responsible for capturing temporal dependencies in the input signal. The model classifies the processed signal into two classes: PD and control.

The CNN architecture comprises several layers, including convolutional layers, activation functions (e.g., ReLU), and pooling layers. These layers are responsible for learning the spatial features of the breathing signals. The LSTM layer, which follows the CNN, focuses on learning the temporal relationships between the features extracted by the CNN.

Model Training:

The model was trained using the training dataset, with the loss function set to binary cross-entropy and the optimizer configured to Adam. The training was conducted over a predetermined number of epochs with an early stopping criterion to prevent overfitting. The model's performance was assessed using a validation set during training, ensuring that the model generalized well to unseen data.

Model Evaluation:

After training, the model was evaluated using the testing dataset, which was not used during the training process. The performance of the model was assessed using precision, recall, and F1-score metrics for both PD and control subjects, providing a comprehensive view of the model's ability to classify the breathing signals accurately.

Model Interpretability:

To gain insight into the model's decision-making process, we visualized the feature maps generated by the CNN layers. This allowed us to identify the regions of the input signal that the model found most informative for classification, providing a deeper understanding of the relationship between the breathing patterns and the presence of PD.

RESULTS:

My deep learning model, which combined a CNN and an RNN, was trained and evaluated using a dataset containing the respiratory breathing patterns of individuals with PD and age-matched control subjects during sleep. The model was designed to classify the two-dimensional signals representing the subjects' respiratory patterns into two classes: PD and control. The performance of the model was assessed using precision, recall, and F1-score metrics.

Control Subjects:

The model achieved a precision of 90% for control subjects, indicating that 90% of the subjects classified as control were indeed healthy individuals. The recall for control subjects was 70%, suggesting that the model was able to correctly identify 70% of the actual control subjects in the dataset. The corresponding F1-score, which combines both precision and recall, was 0.79 for control subjects, indicating a balanced performance in identifying healthy individuals.

Parkinson's Patients:

For Parkinson's patients, the model achieved a precision of 70%, meaning that 70% of the subjects classified as having PD were true positive cases. The recall for Parkinson's patients was 90%, demonstrating the model's ability to correctly identify 90% of the actual Parkinson's patients in the dataset. The F1-score for Parkinson's patients was 0.79, showing a balanced performance in detecting individuals with PD.

Confusion Matrix:

A confusion matrix was also generated to provide a more detailed view of the model's performance. The matrix revealed the following results:

True Positives (Parkinson's): 90% of the actual Parkinson's patients were correctly identified by the model.

True Negatives (Control): 70% of the actual control subjects were correctly identified by the model.

False Positives: 30% of the subjects classified as having PD were actually control subjects.

False Negatives: 10% of the subjects classified as control subjects were actually Parkinson's patients.

Overall, the results indicate the potential of the proposed method in detecting early PD based on sleep respiratory breathing patterns. The model's high recall for Parkinson's patients is particularly noteworthy, as it highlights the effectiveness of the model in identifying true positive cases, which is crucial for diagnostic applications.

DISCUSSION:

My study demonstrates that combining smartphone technology with deep learning can provide a non-invasive, cost-effective, and accurate method for early detection of Parkinson's disease. The deep learning model, which combines a CNN and an RNN, effectively classifies breathing patterns during sleep into two classes: PD and control.

The achieved precision and recall scores indicate the model's ability to identify both Parkinson's patients and control subjects with high accuracy. The high recall for Parkinson's patients suggests that the model is particularly effective at detecting true positive cases, which is crucial in a diagnostic context to avoid false negatives.

However, there are some limitations to my study. First, the data used in this research was obtained from a single source, which may limit the generalizability of the findings. Future studies should consider using larger and more diverse datasets to validate the model's performance across different populations. Second, the model's performance may be influenced by factors such as sleep disorders or other respiratory conditions, which were not accounted for in this study. Future research should address these potential confounders and investigate the model's performance in a real-world setting with a broader range of subjects.

CONCLUSION:

In conclusion, this study presents a promising approach for the early detection of Parkinson's disease using smartphone-generated ultrasonic rays to capture respiratory breathing patterns during sleep. The deep learning model, which combines a CNN and an RNN, demonstrates high precision and recall scores in classifying the breathing signals into Parkinson's and control subjects. By leveraging smartphone technology and deep learning, this approach has the potential to revolutionize PD diagnosis, enabling earlier detection and improved disease management. Further research is needed to validate the model's performance in larger and more diverse populations and to account for potential confounding factors.