Diagnosing Parkinson’s Disease Using Deep Recurrent Neural Networks on Spiral Hand Drawings

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Abstract

Parkinson’s Disease is one of the most common disease of the elderly with motor symptoms including shaking and stiffness in hand movement. Static Spiral Test has proven to be a benchmark test for people with Parkinson’s Disease because it gauges the motor capabilities of the subject. Previous machine learning classification models are limited to Statistical Machine Learning models on spiral drawings dataset primarily because the small size of the dataset. We propose a Recurrent Neural Network approach for Parkinson’s Disease diagnosis based on Static Spiral Test with satisfactory results. Moreover, the accuracy of the model may be increased with the availability of more temporal data.

Keywords: Parkinson’s Disease, Static Spiral Drawings, Long Short Term Memory, Deep Neural Networks, Machine Learning, Classification.

1. Introduction

Parkinson’s Disease is a long term degenerative disorder of the central nervous system. Its symptoms include shaking, rigidity, slowness of movement and difficulty with walking. Apart from physical problems, thinking and behavioral problems may also occur leading to depression, anxiety and dementia in the later stages of the disease. A common disease in the elderly, Parkinson’s Disease is currently incurable. However, an early diagnosis may increase the quality of life of patients. Due to the complex symptoms of the disease, its clinical diagnosis is challenging. Even today, identifying an exam that can diagnose a patient with Parkinson’s Disease accurately enough is not an easy task. In that regard, digital analysis of spiral hand drawings has been proven to be a valuable avenue of research for the detection of motor syndromes. Numerous attempts at diagnosing Parkinson’s Disease using Computer Vision and Image Processing primitives have been made. Using wearable sensors (Rigas et al., 2012), and feeding the signals to two Hidden Markov Models achieved a diagnosis accuracy of 87%. Using the speech dataset (Sakar et al., 2013) and training SVM classifier with RBF kernel yielded 82.14% accuracy. On the spiral drawing dataset, statistical Machine Learning models have achieved an accuracy of 86.87% (Akyol, 2017). However, the use of deep neural networks with spiral hand drawing has been fairly limited, purely because the amount of raw data available to feed to the neural networks is scarce.

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We propose to train a Long Short Term Memory (LSTM) model on the Static Spiral hand-drawing dataset which shows the potential to achieve state-of-the-art accuracy when used with larger datasets.

2. Method

2.1. Data

The data set used for this study comprises of the result of a Static Spiral Test of 62 individuals with Parkinson’s and 15 control subjects (Isenkul et al., 2014). The Static Spiral Test required the subjects to trace a static three wound Archimedean Spiral on a digitized tablet and recorded 5 attributes at numerous instants for each subject namely:

\[ x, y, Pressure, GripAngle, Timestamp \]

A sample image rendering of the Static Spiral Test of a patient with Parkinson’s is given in Figure 1

![Static Spiral Test of a Patient with Parkinson’s Disease](image)

Figure 1: Static Spiral Test of a Patient with Parkinson’s Disease

2.2. Preprocessing

Fundamentally, the scales for the various features were different. They were thus standardized to zero mean and unit standard deviation using the Z-score. The input feature matrix for each individual was padded to 3000 features. Thus, the transformed input shape became: \(77 \times 3000 \times 6\). These data labels were then shuffled randomly to inhibit bias and/or overfitting in the network. A small portion of data was kept aside as validation data which amounted to 25% percent of the dataset (19 labels).

2.3. Architecture

The Neural Network architecture was a 2-stage deep neural network. The first layer was the LSTM layer consisting of 6 hidden units. The final layer was the fully connected layer with 30 hidden layer units which compared the loss and relayed the loss back to the LSTM layers using Back-propagation. We used the binary crossentropy loss for the fully connected layer. The experimental results showed that an exponential activation function provided high accuracy and low loss. The optimiser for the dense layer was chosen to be rmsprop for similar reasons.
2.4. Training

The LSTM network was trained end-to-end for 150 epochs (lr=0.01). Altering the learning rate from the initial rate had little impact on the outcome. Similarly, enforcing dropout in the neural network also didn’t change the accuracy. The best results were obtained by training the model in a 10-fold cross validation scheme, leading to an accuracy of 69.8%.

3. Conclusion and Future Work

Although the deep neural networks do have room for improvement, it can be assessed that a deep Recurrent Neural Network for classifying people with Parkinson’s using Static Spiral hand-drawing may provide results on par or in some cases even better than Statistical Machine Learning models. It is easy to see that the major disability for learning under a small data set is the chance of over-fitting which needs to be handled at every stage. Perhaps with the availability of a large corpus of data, LSTMs may provide a more reliable diagnosis than other machine learning models because of its ability to remember previous states while learning. With more recent research such as using feature extraction on the spiral drawing dataset (Mucha et al., 2018) opens up doors for using LSTMs.
References


