

# MRI IMAGE SYNTHESIS FOR THE DIAGNOSIS OF PARKINSONS DISEASE USING DEEP LEARNING

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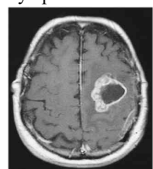
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## INTRODUCTION

### BACKGROUND

Parkinson's Disease is a progressive neurodegenerative disorder and is the most common movement disorder. Symptoms of this neurological disease, such as resting tremor, balance problems, and bradykinesia, have a slow but progressive onset. Current diagnosis methods for Parkinson's Disease include neurological data analysis to search for symptoms.



Extremely low birthweight group			
	None	Slight	Pronounced
Fig. 100	4	35	12
Motor movements	14	16	21
Associated movements			
Other signs			
Hypertonia of limbs	45	7	1
Tremulousness	36	15	0
Dystonic movements	23	25	2
Unilateral clonus	5	19	20
Plagiopnea test	46	5	2
Prone placing	36	16	14
Prone separation	25	14	14
Prone to a finger	25	15	13
Clinic-separation	42	8	9
Clinic-separation	20	17	16
Heel walking			
Associated movements	19	15	19

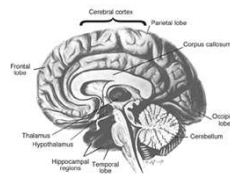


Figure 1: Depicting the various parts of the Brain (NIH).

Figure 2: Diagnosis pipeline for Parkinson's Disease. (1) Collection of neurological data including MRI scan, (2) Numerical data from neurologists is also included. (3) A pathologist analyzes the data and determines a diagnosis for the disease (NIH).

From the data collected, diagnoses made by pathologists is purely from knowledge of the prevalence of supposed symptoms. This leads to many diagnoses being incorrect, as either symptoms have not appeared yet, or the symptoms are of another disease, culminating in a clinical diagnosis accuracy of 80.6% (Rizzo, 2016).

In this work, deep learning with Convolutional Neural Networks (CNNs) is applied to analyze MRI images for the automatic diagnosis of Parkinson's Disease. The diagnosis models will be paired with Segmentation models and Auto-Encoders to provide underlying data potentially important to pathologists.

### STATISTICS

**10 Million:** worldwide Parkinson's disease diagnoses

**21 Million:** estimated number of people affected with Parkinson's

**18.7 years:** decrease of life expectancy for Parkinson's patients

### ACKNOWLEDGEMENTS & REFERENCES

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Tapert, S., Cadwell, L., & Burke, C. (2005). Alcohol's Effects on the Adolescent Brain: What Can Be Learned From Animal Models. *Alcohol Research & Health*.

Rizzo G, Copetti M, Arcuti S, Martino S, Fontana A, Logroscino G. Accuracy of clinical diagnosis of Parkinson's disease: a systematic review and meta-analysis. *Neurology*. 2016;86:566-76. [PubMed]

Snoek J., Larochelle H., & Adams R. (2012). Practical Bayesian Optimization of Machine Learning Algorithms. *Advances in Neural Information Processing Systems*.

## METHODS

### DATASET INFORMATION

The data for this experiment was retrieved from LONI Image Data Archive's Parkinson's Progressive Markers Initiative (PPMI). The dataset included thousands of MRI images, and multimodal genetic data. However, the data was from different devices and came in multiple sizes, rendering around 80% of the images useless.

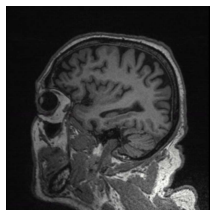


Figure 3: Example slice of MRI from the PPMI Dataset (LONI).

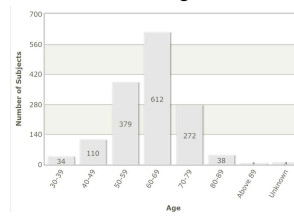


Figure 4: Distribution of Ages of Subjects participating in the PPMI study that have data collected (LONI).

### NETWORK ARCHITECTURE

The segmentation neural network used was similar in structure to the U-Net, and the GAN and classification models were organically produced. The hyperparameter and feature values were chosen by the Bayesian optimization program Spearmin (Snoek et al).

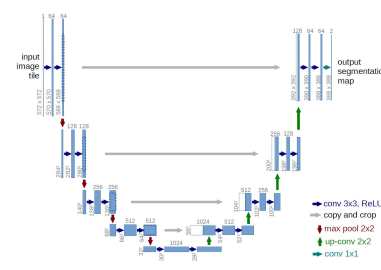
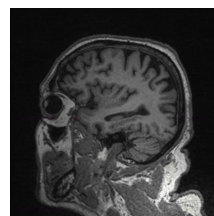


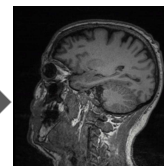
Figure 5: Graphical depiction of the U-Net architecture, where the input is a square image and the output is a mask of the same dimensions (Ronneberger et al).

## CLASSIFICATION APPLICATION PIPELINE

MRI (3 Dimensional)



GAN



Artificial MRI (3 Dimensional)

Compiled Dataset

CNN

Predicted Diagnosis

Figure 6: The pipeline of the Parkinson's Profiler system. The input MRI image is used in 2 places -- in the GAN to generate more inputs, as well as the data used to train the classifier. The data is then used to train a Convolutional Neural Network to calculate predicted diagnoses of the images.

### NETWORK TRAINING

For the Medical Image Synthesis program, the 614 collected MRI images of 256x240x176 pixels were separated into the training and testing groups at a 75%-25% split. These images were fed into a pair of a discriminator and generator, the generator working to generate random images from a seed and the discriminator working to separate the real from the fake. The goal of the generator is to trick the discriminator into believing the fake images are real ones. The pair was trained over 600 epochs on 1 NVIDIA K80 GPU.

For the image classifier, the 700 MRI images (86 generated, 614 collected) of 256x240x176 pixels were separated into the training and testing sets in a 75%-25% split. The data was trained on 1 NVIDIA K80 GPU for 25 epochs using Early Stopping procedures, ultimately ending at 13 epochs, with 4 hours per epoch.

Table 1: The values associated with 5 pertinent hyperparameters, chosen on account of the training data.

Hyperparameter Values				
Base LR	LR Policy	Gamma	Momentum	Weight Decay
0.001	Step	1.0	0.5	0.01

## FINDINGS AND CONCLUSION

Table 2: The accuracy and loss associated with the Training and Testing sets.

Results			
Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
97.523	0.0529	96.571	0.0823

- Examining a larger dataset had significant returns on testing accuracy – an increase of approximately 5.2%. The generated data was only used in training, and did not have any affect on the test set to ensure the final accuracy is reported on real images.
- This work represents the first study to artificially synthesize medical data for the purpose of improving classification accuracy.



Figure 7: Example Generated Images used to augment the original dataset, showing various layers of the MRI.