PDGAN: Using Generative Adversarial Networks to Improve the Diagnosis of Parkinson’s Disease

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First Iteration Prediction Framework

Model Selection and Creation

Initial Training Results

Problem: Lack of Available Training Data

Image Generation for Data Augmentation

GAN Image Generation

Determining Number of Generated Images

Deep Learning Improvements to Create PDGAN

Additions to Tackle Vanishing Gradient Problem

Development of a Custom PDGAN Model

Final Training Results

Because the images that are generated may not actually be correct brain images, a brain segmentation model was trained to ensure the boundary of the brain in generated remained intact.

Figure 16: An example of the optimization choosing points to test

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Figure 22: Image Depicting the U-Net Design

Brain Border Segmentation Framework

Validation Reasoning

Addition 1: Bayesian Optimization

To increase the accuracy of the model further, the model parameters were tuned using the Spearmint package, optimizing under the number of filters per layer, learning rate, and other related quantities.

Figure 23: Image Depicting how increasing the number of generated images and its effect on increasing accuracy.

Addition 2: Sparsely Connected Networks

Sparsely connected networks allow the machine learning model to explain small amounts of performance variation because these occur as well as a potential for overfitting. Using sparsely connected networks reduced training time by up to 98.4%.

Figure 11: Graph depicting how increasing the number of generated images and its effect on increasing accuracy.

Model Incorporated the optimizations described above, solving most common problems affecting deep learning models, specifically to decrease training time. This model incorporated the "offline" models because it was a fully 3D convolutional network.

Figure 8: LeNet model architecture (Source: Medium)

3 models (LeNet, VGG-16, ResNet-50) were tested for accuracy, sensitivity, and specificity through 15 epochs of training, each lasting around 8 hours on a NVIDIA Tesla K80 GPU.

Figure 9: Graph depicting the performance of the ImageNet challenge, showing capability to see patterns in large and diverse amounts of data.

Evidently, the ROC curve score of 0.92 is higher than the first attempt, which was at 0.148. Although this accuracy was an increase compared to clinical observations, it did not reveal any further increase of accuracy.

Figure 19: Image Depicting the concept of ’U-Shelf’-off the shelf models.

To solve some of the problems, a new PDGAN model was designed to be simpler to control the vanishing gradient problem, but still capable of avoiding complex MRI-specific problems.

Figure 17: Few of the various parameters passed to the model including learning rate, epochs, number of neurons per layer, and other related quantities.

Addition 3: Residual Learning

Residual learning is a solution to the traditional vanishing/exploding gradient problem of stacking layers. As more layers are added, the residual learning ability is capable of decreasing training error, increasing training speed, and reducing overfitting and generalization error.

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Figure 10: Image depicting the concept of residual learning (Source: Medium)

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**Parkinson's Disease**

In the second most prevalent neurodegenerative disease, affecting 10 million people worldwide, Parkinson’s disease (PD) has been linked to a 30-40% increased risk of Alzheimer's disease, cognitive dysfunction, hallucinations, paranoia, and tremors.

**Diagnosis Challenges**

- **Clinical Diagnoses:** The accuracy of diagnosing PD is low due to the progressive nature of the disease, which is characterized by tremors, rigidity, bradykinesia, and a gait disorder.
- **Imaging:** MRI scans of the brain can be used to detect structural changes, but these are not always consistent with the clinical diagnosis.
- **Genetic Testing:** Genetic testing can help identify mutations associated with PD, but it is not always conclusive.

**Problem Definition**

From the data collected, diagnoses related to pathologies purely from MRI images can be used to develop a computational pipeline that could help identify PD at an earlier stage. This pipeline should be able to analyze anatomical MRI scans, detect physical changes associated with PD, and provide accurate diagnoses without being biased by clinical information.

**Objectives**

- **Diagnosis Challenges:** By accurately and automatically predicting a diagnosis on subject with or without Parkinson’s Disease based off of MRI scans.
- **Accuracy:** Determine the best forms of models capable of being modular and accepting any input shape.
- **Computational diagnoses are effective:** This project aims to develop a computational system that can accurately diagnose PD using MRI scans.

**Methods**

**Dataset:** The MRI database consists of anonymized MRI images of patients with Parkinson's disease and healthy controls.

**Image Preprocessing:** To improve the diagnostic accuracy of MRI scans, the images were preprocessed to remove noise and enhance the visibility of structural changes.

**Medical Dataset:** The dataset includes MRI scans of patients with Parkinson's disease and healthy controls, which were used to train the computational model.

**Overview of Solution**

There are two major challenges for PD diagnosis: (1) differentiation of early PD from healthy controls and (2) distinguishing between PD and other diseases. To address these challenges, the proposed solution uses a combination of generative and classification networks.

**PDGAN**

PDGAN (Parkinson’s Disease Generative Adversarial Network) is a deep learning approach that generates realistic PD images from non-PD images. It is trained on a corpus of images to analyze anatomical MRI scans and predict the presence of PD.

**Results**

- **GAN Training Results:** After 148 epochs, the GAN’s training loss converged, and the accuracy reached 81% on the test set.
- **Brain Segmentation Results:** The accuracy of the Brain Segmentation model was 82%, and the training loss decreased significantly.

**Classified Predictor Results**

- **PDGAN model:** Achieved an accuracy of 96.91%, which is significantly higher than the baseline accuracy of 60.01 through the T-Test for Independent Means.

**Discussion**

The primary objective of this project was to develop a computational pipeline for PD diagnosis. The pipeline incorporates a generative and classification network to predict the presence of PD. The pipeline was trained on a corpus of images to analyze anatomical MRI scans and predict the presence of PD.

**Conclusion**

- **Contributions:** PDGAN is a data-driven approach to diagnosing Parkinson's disease. It leverages the power of generative and classification networks to provide accurate and reliable diagnoses.
- **Future Work:** Further experimentation with different models and datasets is needed to improve the accuracy of the computational model.

**References**