The Parkinsons Pathfinder

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Link to Project.

Introduction

Parkinson's is a complex disease that challenges the lives of many in the way that it works. Specifically, it works by causing a "significant reduction in dopamine levels, which disrupts motor control and leads to symptoms such as tremors, muscular rigidity, bradykinesia, postural instability, and difficulty walking"[5].

A big part of detecting Parkinson's and detecting it early is to look at MRI scans of individuals and identify abnormalities that indicate Parkinson's. The rationale behind this project is to create a model which can utilize the brain scans of individuals and determine whether they have Parkinson's disease or are healthy. The rationale behind using a deep learning approach is because CNNs are state-of-the-art image classification models that can understand subtle patterns that radiologists might miss.

Background & Related Work

Several previous studies have had similar objectives in using deep learning models to detect Parkinson's disease using magnetic resonance imaging (MRI).). The first paper by Shokrpour [5] conducted a comprehensive review of the various datasets and algorithms used by previous researchers. They investigated the work of acoustic data, biomarkers, medical imaging, movement data, and multi modal datasets. While the paper by Manal Alrawis [1] used a deep learning approach as well, but went beyond the traditional CNN's. Using their model across three data sets and achieving an accuracy over 95 percent.

However, an alternative approach presents itself as well where the paper published by Yan Chang[3] decided to omit MRI models and take a different method for detection. Upon finding two other papers written by Megan Courtman[4], and Milton Camacho[2], I saw that they used MRI scans and 3rd dimensional CNN's, respectively, to detect Parkinson's early.

As a whole, it is clear that Parkinson's detection is doable by Deep Learning Networks, and CNN's could be considered a reasonable approach. For the benchmark, I know that prior models also exist such as ResNet which is actively used in medical imaging, however these are a benchmark, not a baseline.

Data Processing

In the preliminary data exploration that I have conducted I know that I have access to about 831 MRI scans(shown in GitHub), and about 221 of these are scans with Parkinson's Disease. I intend to split the data set into 80-20 splits. Where 80 percent are used for training.

I also intend to transform all the data to 128x128 pixels and normalize the pixel values so that it makes the model easier. The size is historically considered large enough to preserve features but small enough to ensure computational capacity. For normalization, I want the scanner to focus on features, not intensity, and this will enable the learning of disease patterns.

One consideration I'm taking is to potentially rotate, or flip the images to increase my dataset, but this is still subject to change based on feedback.

Illustration

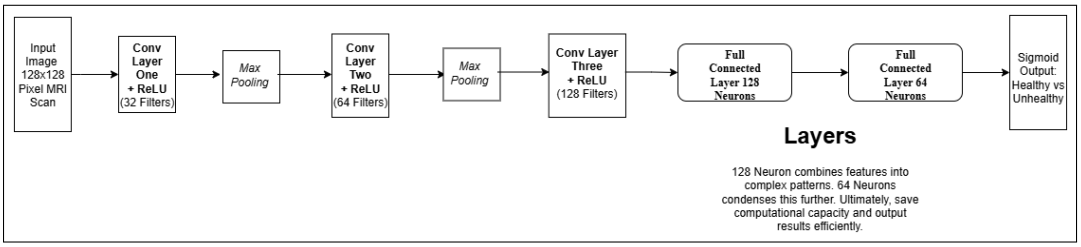

Figure 1: CNN architecture with three convolutional layers, pooling, fully connected layers, and sigmoid output.

Architecture

For the architecture of my model I am using a CNN, as shown in Figure **??**. Most of the hyper-parameters will be tuned experimentally, regardless, I believe three layers would be good for my dataset, and is considered ideal for medical imaging. The first layer will shape out blobs and shapes. The second layer will be textures and distinguishable features. With a third layer focusing on brain structures and regions. As shown in Figure **??** above. I personally intend to use ReLU activation functions due to their ability to avoid vanishing gradients through multiple layers, and its commonality for CNN's. Pooling layers will also be added to preserve the key features, and to ensure dimensionality across layers. Meanwhile hyper-parameters such as learning rate, and filter size will also be tuned during testing. To reduce overfitting, due to the smaller dataset, I'll also be implementing techniques such as dropout. Finally, I will output healthy or unhealthy using a sigmoid output. As a result this will allow me to ultimately classify between healthy, and unhealthy patient MRI scans even for a smaller sized dataset while keeping computational costs low.

Baseline Model

The baseline model for this project will be a simple ANN, the architecture will take my input of MRI scans of (128x128 pixels),consists of two hidden layers, and one output layer. The first layer is 128 neurons, and the second will be 64 neurons. This is done so that I can capture enough features within the first layer, and use the learned representations within the second layer. For my activation function in the baseline model I will also be using the ReLU activation function. Meanwhile, the final output layer will most likely be a sigmoid function which classifies between healthy, and unhealthy. Here the ANN is my baseline because unlike the CNN, it won't be able to determine distinct patterns such as: edges, brain regions, and textures. This is because ANNs treat each pixel separately, and thus ignore the structure of MRI images. I will compare my baseline model to the CNN using the F1-Score, accuracy, precision and recall.

Ethical Considerations

First and foremost this is not for medical imaging purposes, and is simply a research project I found interesting. I also recognize that due to the limiting size of my dataset, that it is very possible that false negatives, and false positives occur. This is a risk because it essentially jeopardizes a critical diagnosis. Lastly, I know that the imbalance in the data may cause me to need weighting methods, so I will consider those in my implmentation. Both of these are considerations to be taken heavily as they could cause serious issues if a model like this is purely used for diagnosis.

References

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[3] Y. Chang et al. Deep learning for parkinson's disease classification using multimodal imaging to differentiate parkinson's disease from multiple system atrophy. *Frontiers in Neuroscience*.

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[5] Sahar Shokrpour, AmirMehdi MoghadamFarid, Sepideh Bazzaz Abkenar, Mostafa Haghi Kashani, Mohammad Akbari, and Mostafa Sarvizadeh. Machine learning for parkinson's disease: a comprehensive review of datasets, algorithms, and challenges. *npj Parkinson's Disease*, 11(1):187, 2025.