EARLY DETECTION OF PARKINSON'S DISEASE USING MACHINE LEARNING AND CONVOLUTIONAL NEURAL NETWORKS FROM DRAWING MOVEMENTS

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ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative disorder that causes uncontrollable movements and difficulty with balance and coordination. It is highly important for early detection of Parkinson's disease in order for patients to receive proper treatment. This paper aims to aid in the early detection of Parkinson's disease by using a convolutional neural network for PD detection from drawing movements. This CNN consists of 2 convolutional layers, 2 max-pooling layers, 2 dropout layers, 2 dense layers, and a flattened layer. Additionally, our approach explores multiple types of drawings, specifically spiral, meander, and wave datasets hand-drawn by patients and healthy controls to find the most effective one in the discrimination process. The models can be continuously trained in which the test data can be inputted to differentiate between healthy controls and PD patients. By analyzing the training and validation accuracy and loss, we were able to find the most appropriate model and dataset combination, which was the spiral drawing with an accuracy of 85%. With a proper model and a larger dataset for increased accuracy, this approach has the potential to be implemented in a clinical setting.

KEYWORDS

Machine Learning, Deep Learning, Parkinson Disease.

1. INTRODUCTION

Parkinson's Disease (PD) is a progressive disorder of the nervous system marked by tremors, muscular rigidity, and slow, imprecise movement, chiefly affecting middle-aged and elderly people [1]. It is associated with degeneration of the brain's basal ganglia and a deficiency of the neurotransmitter dopamine. Worldwide, around 7-10 million people have Parkinson's Disease [2], making it highly important to diagnose PD accurately in the early stage so that patients can receive proper treatment [3]. Parkinson's disease (PD) is difficult to diagnose, particularly in its early stages, because the symptoms of other neurologic disorders can be similar to those found in PD. Meanwhile, early non-motor symptoms of PD may be mild and can be caused by many other conditions. Therefore, these symptoms are often overlooked, making the diagnosis of PD at an early stage more challenging [4]. To address these difficulties and refine the early detection of PD, different neuroimaging techniques (such as magnetic resonance imaging (MRI), computed tomography (CT) and positron emission tomography (PET)) and deep learning-based analysis methods have been developed [5].

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The rest of the paper is organized as follows: Section 2 describes our research background, direction, and the crucial elements needed in our research in detail; Section 3 presents our approach to solve the problem and relevant details about the experiment we did; Section 4 presents the results and analysis; Section 5 gives a brief summary of other work that tackles a similar problem; finally, Section 6 gives the conclusion remarks and discusses the future work of this project.

2. CHALLENGES

Figure 1 shows a chart of simplified machine learning applications. The research presented in this paper focused on the dark blue boxes as our research direction.

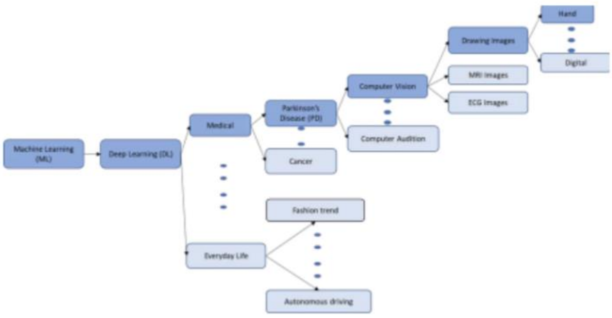

Figure 1. Machine Learning Application

2.1. Machine learning

Machine Learning is the technology of developing systems that can learn and draw inferences from patterns in data which can be applied to many different fields, from data analytics to predictive analytics, from service personalization to natural language processing, and so on [6].

According to Shalev-Shwartz, S. et al. [7], Machine learning can be defined as "using the experience to gain expertise." The learning could be supervised learning, unsupervised learning, etc. Supervised learning is the most common approach and is the approach we utilize in our research.

Supervised learning algorithms try to model relationships between the target prediction output and input features to predict output values for new data based on the relationships learned from the prior data sets. This type of learning is normally related to classification tasks, which is the process of teaching a classifier the relationship between the model's input and output to use this expertise later for un-seen input [8].

2.2. Deep Learning

Because machine learning is unable to meet the requirements due to the complexity of the problems in certain areas, Deep Learning (DL) is gaining popularity due to its supremacy in terms of accuracy. It is an advanced level of machine learning which includes a hierarchical function that enables machines to process data with a nonlinear approach. The deep learning networks are built with neuron nodes connected like the human brain and have many layers, each layer receiving information from the previous layer, trained to perform the desired tasks, and then passing on the information to the next layer [9].

Figure 1 shows that Deep Learning (DL) can be applied to fashion trend forecasting and autonomous driving, as examples for everyday life. Additionally, Deep Learning (DL) has also been applied to pharmaceutical research, such as cancer diagnosis [10] and Parkinson's Disease diagnosis [11] [12].

Within Parkinson's Disease diagnosis, there is research that focuses on computer audition while others focus on computer vision. Within the computer vision domain, the computer can help recognize and visualize electroencephalogram (EEG) signals automatically and help recognize and visualize brain scan images [5]. Some research focuses on the computer analyzing human drawn images [11] [12].

While human drawings can be hand drawn on paper or digitally, this paper's research interest is focused on using computer vision Convolutional Neural Network (CNN) to read/process hand-drawn drawings to help diagnose Parkinson's Disease.

2.3. Convolutional Neural Network

A convolutional neural network (CNN) can be made up of many layers of models, where each layer takes input from the previous layer, applies a filter to the data, and outputs it to the next layer. CNNs run much faster on GPU, and the huge stockpiles of data that have been collected can improve the accuracy of computer vision and NLP algorithms. A CNN consists of several convolutional layers, with each layer including three major stages: convolution, non linear activation (non linearity transform), and pooling (sub-sampling) [13].

2.4. Datasets

Datasets are fundamental in a deep learning system. An extensive and diverse dataset is a crucial requirement for the successful training of a deep neural network. In our research, we explore different CNNs using datasets we downloaded from HandPD [14] and Kaggle [15].

3. SOLUTION

The problem this research trying to solve can be summarized as the following

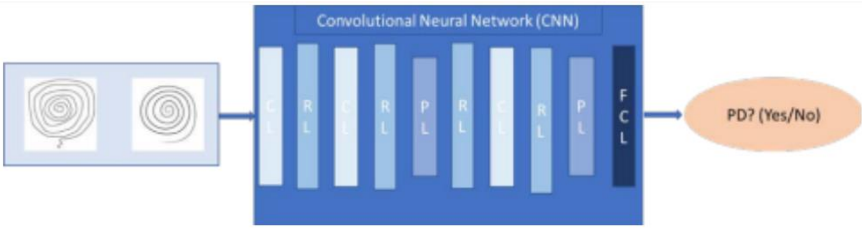

Figure 2. Problem Definition CL: Convolutional Layer, FCL: Fully Connected Layer, PL: Pooling Layer, RL: ReLU Layer

The dataset consists of hand drawn images (spiral/meander/wave) drawn by healthy people and Parkinson's disease patients. The model learns through training and uses a CNN to predict whether the person who drew the image has Parkinson's disease or not. The CNN model has one convolutional layer in front, a fully connected layer at the end, and a variable number of convolutional layers, max-pooling layers, and ReLU layers in between.

We downloaded HandPD dataset from [14]. The dataset contains 92 individuals, divided into 18 healthy people (Healthy Group) and 74 patients (Patients Group). Some examples are shown below. The brief description is the following:

● Healthy Group: 6 male and 12 female individuals with ages ranging from 19 to 79 years old (average age of 44.22±16.53 years). Among those individuals, 2 are left-handed and 16 are right-handed.
● Patient Group: 59 male and 15 female individuals with ages ranging from 38 to 78 years old (average age of 58.75±7.51 years). Among those individuals, 5 are left-handed and 69 are right-handed.

Therefore, each spiral and meander dataset is labeled in two groups: the healthy group containing 72 images, and the patient group containing 296 images. The images are labeled as follows: ID_EXAM-ID_IMAGE.jpg, in which ID_EXAM stands for the exam's identifier, and ID_IMAGE denotes the number of the image of the exam.

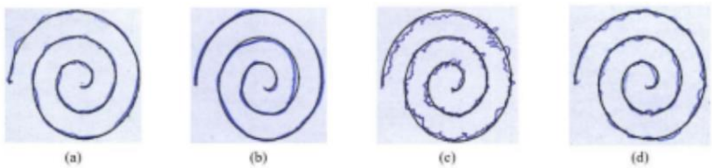

Figure 3. Some Examples of Spirals Extracted from the HandPD dataset [11]

Figure 3 shows (a) 58-year-old males (b) 28-year-old female individuals of the control group, (c) 56-year-old males, and (d) 65 -year old female individuals of the patient group.

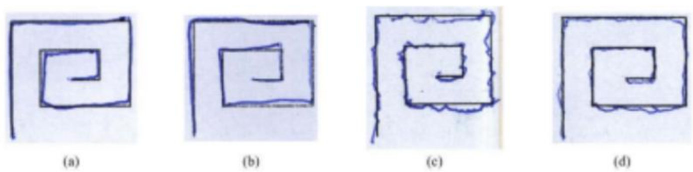

Figure 4. Some Examples of Meanders Extracted from HandPD Dataset[11]

Figure 4 shows (a) 58-years old male (b) 28-years old female individuals of a control group and (c) 56-years old mail and (d) 65-years old female individuals of a patient group.

All the data in HandPD dataset is in *.jpg format. For the exploration, we did some pre-processing including resizing, blurring, eroding, diluting, and color space converting (cv2.cvtColor() method).

The second dataset is downloaded from Kaggle [15]. The dataset has two patterns: wave and spiral. They are all in *.png format. The dataset is split into training and testing data. No personal information such as age and gender are available. We did not do any pre-processing for the data.

Wave drawing: there are 72 total wave drawings in the training data -- 36 drawn by Parkinson's disease patients and 36 drawn by healthy people. There are 30 total wave drawings in the testing data -- 15 drawn by Parkinson's disease patients and 15 drawn by healthy people. Figure 5 shows example drawings by Parkinson's disease patients and Figure 6 shows example drawings by healthy people.

Figure 5. Wave Drawing Sample by Parkinson's Disease Patients from Kaggle [15]

Figure 6. Wave Drawing Sample by Healthy People from Kaggle [15]

Spiral drawing: there are 72 total spiral drawings in the training data -- 36 drawn by Parkinson’s disease patients and 36 drawn by healthy people. There are 30 total spiral drawings in the testing data -- 15 drawn by Parkinson’s disease patients and 15 drawn by healthy people. Figure 7 shows example drawings by Parkinson’s disease patients and Figure 8 shows example drawings by healthy people.

Figure 7. Spiral Drawing by Parkinson's Disease Patients from Kaggle [15]

Figure 8. Spiral Drawing by Healthy People from Kaggle [15]

Our model consists of 2 convolutional layers, 2 max-pooling layers, 2 dropout layers, 2 dense layers, and one flattened layer. All the activation functions are ReLU. Figure 9 shows our model. We chose this particular CNN architecture since it gives good results [11] [27].

The dropout layer is a technique introduced by Srivastava et al. [31]. This layer aims to avoid overfitting by randomly ignoring randomly some neurons from the previous layer. We inserted the dropout layers to improve the performance of our model.

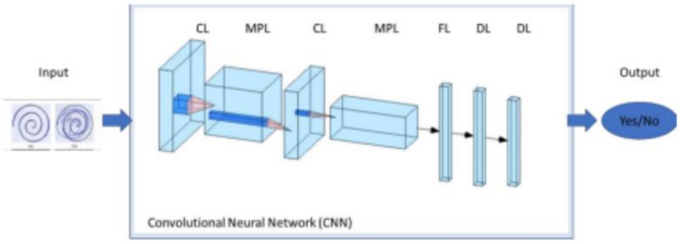

Figure 9. The Proposed CNN Architecture

4. EXPERIMENT

Figure 10 shows the training and validation accuracy and loss. The dataset we used is the spiral dataset downloaded from HandPD [14] without pre-processing. The CNN we used is the one shown in Figure 9. As we can see, it has a severe overfitting problem. To resolve this issue, we added dropout [31] after max-pooling. Figure 11 shows the validation accuracy and loss after dropout was added, preventing the model from overfitting and minimizing validation loss.

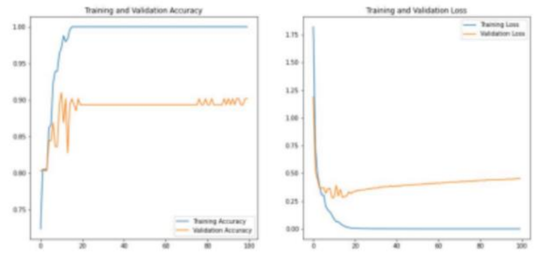

Figure 10. Pre-processing Spiral Data from HandPD [14] Using the Model Shown in Figure 9

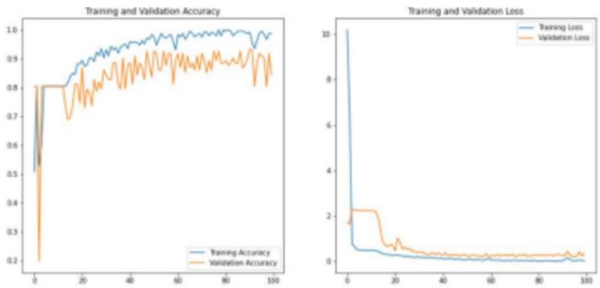

Figure 11. Spiral Data from HandPD [14] with Two Dropout Layers Added after Max-pooling

To see the effects of different drawing patterns, we used two different patterns from the same dataset with the same CNN, with dropout added after max-pooling. Figure 11 uses spiral data from HandPD while Figure 12 uses meander data from HandPD. Comparing Figure 11 and Figure 12 we can see that both patterns generate similar validation accuracy and validation loss results, with the spiral slightly more accurate.

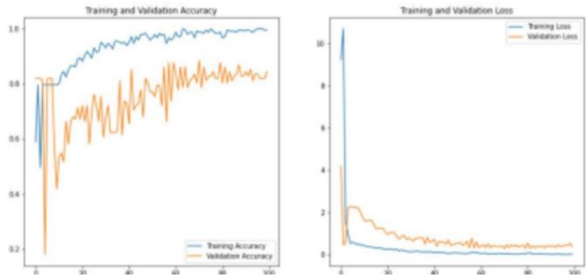

Figure 12. Meander Data from HandPD [14] with Two Dropout Layers Added after Max-pooling

Figure 13 shows a CNN model proposed by M. Alissa [27]. It consists of 6 convolutional layers, three max-pooling layers, three dense layers and one flatten layer. It’s much more complicated and the training/validation time is much longer. We ran both meander data from HandPD (shown in Figure 14) and spiral data from HandPD (shown in Figure 15).

The comparison shows that even though our proposed CNN model is much simpler, it generates better results. This shows that we need a suitable CNN, not necessarily one that is more complicated.

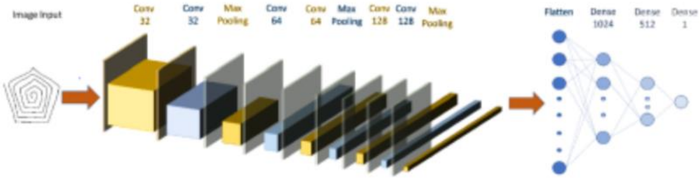

Figure 13. CNN Model Proposed by M. Alissa [27]

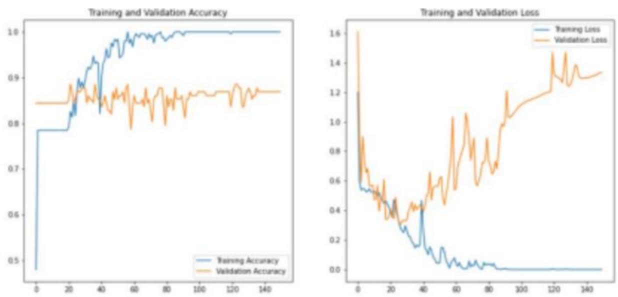

Figure 14. Meander Data from HandPD [14] using CNN Shown in Figure 13

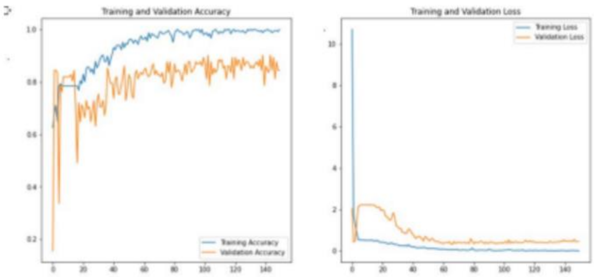

Figure 15. Meander Data from HandPD [14] using Our Proposed CNN shown in Figure 9

Using the same CNN shown in Figure 9, Figure 15 uses pre-processed meander data from HandPD, with added post processing. The results with added post processing are shown in Figure 16. Comparing Figure 15 and Figure 16, the post-processed data did not generate better results.

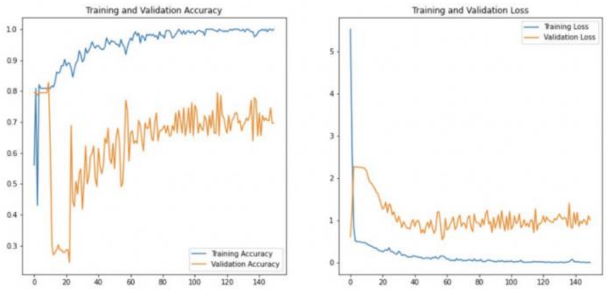

Figure 16. Post-processed Meander Data from HandPD [14] using CNN shown in Figure 9

To compare different datasets, we ran experiments with wave and spiral data from Kaggle using the CNN shown in Figure 9. The wave data results are shown in Figure 17, while the spiral data results are shown in Figure 18. Because the data from Kaggle is in *.png format, the dataset itself is much smaller and not much pro-processing could be done. Therefore, the results are not as accurate as when we use the dataset from HandPD.

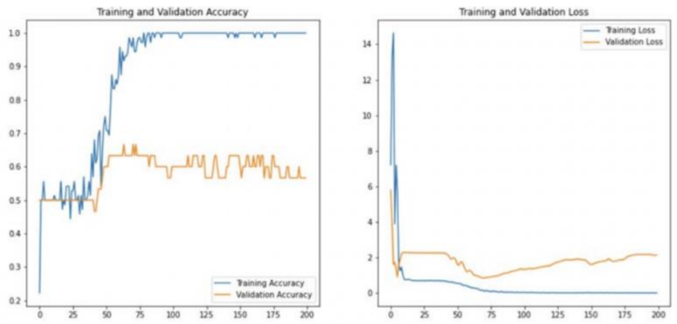

Figure 17. Wave Data from Kaggle [15] using CNN Model in Figure 9

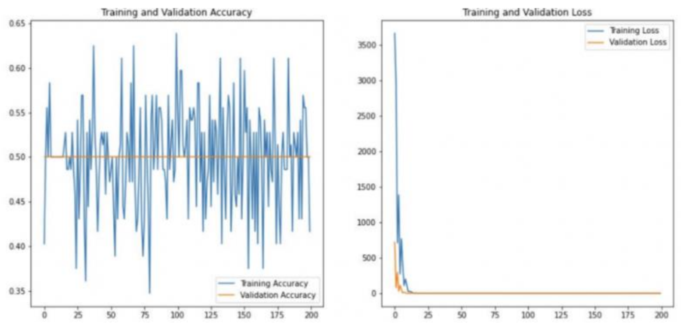

Figure 18. Spiral Data from Kaggle [15] using CNN Shown in Figure 9

5. RELATED WORK

Several researchers have worked on the diagnosis of Parkinson's Disease by using machine learning methods, e.g. diagnosis using voice, diagnosis using brain scan images, diagnosis drawings such as meander patterns, spirals, waves, etc.

J. Mei et al. [16] did a review of literature on machine learning for the diagnosis of Parkinson's disease, using sound, MRI images, and hand-drawn images. It searches IEEE Xplore and PubMed. It reviewed research articles published from the year 2009 onwards and summarized data sources and sample size.

The public repositories and databases include HandPD [14], Kaggle dataset [15], the University of California at Irvine (UCI) Machine Learning Repository [17], Parkinson's Progression Markers Initiative (PPMI) [18], PhysioNet [19], etc.

Quite a few researchers use magnetic resonance images (MRI) or their variations as their research dataset. Noor et al. [5] surveyed the application of deep learning in detecting neurological disorders from magnetic resonance images (MRI) in the detection of Parkinson's disease, Alzheimer's disease, and schizophrenia.

E. Huseyn et al. [20] [21] used MRI images as their dataset. S. Chakraborty [22] and X. Zhang [23] has used a dataset from Parkinson's Progression Markers Initiative (PPMI). Z.Cai et al. [24] used an enhanced fuzzy k-nearest neighbor (FKNN) method for the early detection of Parkinson's Disease based on vocal measurements. L. Badea et al. [25] explored the reproducibility of functional connectivity alterations in Parkinson's Disease based on resting-state fMRI scans images.

Pereira et al. did a series of research on automatic detecting Classify Parkinson's disease for many years. At first, they used non-deep learning algorithms in diagnosing PD [26]. They collected/constructed a public dataset called "HandPD" [14]. Based on this dataset, they compared the efficiency of different hand drawn patterns in the diagnosis of PD [11]. Their results show that the meander pattern generates more accurate results compared to the spiral pattern. However, in our research, the spiral and meander patterns generate similar results when they are trained and tested through the same CNN.

Later, they explored the use of CNN on the images extracted from time-series signals and used three different CNN architectures, ImageNet, CIFAR-10, and LeNet as baseline approach [12].
In her master project, M. Alissa [27] used non-public datasets (spiral pentagon dataset) to evaluate the efficiency of two different neural networks (Recursive Neural Networks(RNN) and Convolutional Neural Networks (CNN)). We built a CNN similar to hers and used the dataset from HandPD [14] and Kaggle [15] to evaluate different CNNs and different datasets.

Gil-Martin et al. [28] presented a method to detect Parkinson's Disease from drawing movements using Convolutional Neural Networks. He used the dataset from the UCI machine learning repository as input data, applied signal-processing (sampling with 100 Hz and 140 Hz, resampling with 110 Hz, perform Hamming windowing and FFT) to generate preprocessed data, and used this data to train/validate the CNNs.

M.E. Isenkul et al. [29] designed an improved spiral test dataset using a digitized graphics tablet for monitoring Parkinson's Disease. Digitized graphics have more information, including timestamps, grip angles, and hand pressure, etc. The significance of that can be investigated in future work.

P.Zham [30] presented a dataset at Kaggle [15] with waves and spirals. He used a composite index of speed and pen-pressure to distinguish different stages of Parkinson's Disease.

6. CONCLUSIONS

Our results show that to get the best results from a deep learning system, we need a good dataset and a suitable CNN, rather than a complicated one. Furthermore, not all pre-processing led to better results.

Bigger datasets: Both HandPD and Kaggle datasets are too small, containing not enough data. To train and make a better model, we need to collect more data, possibly with an app or a collaboration with a hospital/organization [31].

Imbalanced datasets: The data from HandPD and Kaggle are imbalanced as we described in section 3.2. This might mislead the classifier where our models classified all the test sets as patients' [32]. The solution is to increase the number of images drawn by healthy people using augmentation or downsampling the images drawn by patients. However, both ways have their limitations: the augmentation makes the data not real anymore, while the downsampling makes the dataset smaller.

Model improvement: In the future we can explore other deep learning techniques, such as k-fold cross-validation, multiple-stage deep CNN architecture, etc. [33].

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