



Neurodegenerative Disorder Prediction using ML

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Abstract: Parkinson's disease (PD) is a progressive neurological disorder that significantly impairs motor functions due to the gradual degeneration of the central nervous system. Early detection is crucial to manage and potentially slow down the progression of PD. This study proposes a novel detection system that leverages spiral drawings and Convolutional Neural Networks (CNNs) to improve the accuracy and efficiency of PD diagnosis. Developed using Python and Flask, this system aims to offer a more precise and effective alternative to existing diagnostic methods, potentially enabling earlier intervention and better patient outcomes.

I. INTRODUCTION

Parkinson's disease affects millions worldwide, primarily individuals aged 60 and above. The onset of the disease is often insidious, leading to significant delays in diagnosis. Early detection is critical for instituting therapeutic measures that can hinder disease progression and improve patient outcomes.

Conventional methods for detecting PD include neurological examinations, where clinicians observe patient motor functions. Among these techniques, spiral drawings have emerged as a valuable tool for evaluating motor control and cognitive function in patients with PD. This study proposes the development of a PD detection system leveraging CNNs to analyze spiral drawings, thus offering a more accurate and efficient diagnostic approach.

II. LITERATURE SURVEY

1. **Kamble et al. (2021)** present a study focusing on the use of digitized spiral drawings for Parkinson's disease (PD) diagnosis. By analyzing both static and dynamic spirals drawn by PD patients, they achieved a classification accuracy of nearly 91%. The study applied feature engineering and machine learning classifiers such as Logistic Regression, C-Support Vector Classification (SVC), K-Nearest Neighbor (KNN), and Random Forest Classifier (RFC) to differentiate between PD patients and healthy controls. The research confirms the significant impact of digitized spiral drawings in classifying PD patients and supports future efforts in differential diagnosis .

2. **Chakraborty et al. (2020)** developed a system that uses convolutional neural networks (CNNs) to detect Parkinson's disease from spiral and wave drawings. Their multistage classifier approach combines the predictions from two different CNNs, trained on spiral and wave sketches, with an ensemble voting-based meta-classifier. The model, trained on data from 55 patients, achieved an overall accuracy of 93.3%, an average recall of 94%, an average precision of 93.5%, and an average F1 score of 93.94% .

3. **Das et al. (2021)** explored the use of hand-drawn images for detecting Parkinson's disease. They employed machine learning algorithms to analyze Histogram of Oriented Gradients (HOG) features and deep features from the images, which were then classified using models like k-nearest neighbor, random forest, support vector machine, Naïve Bayes, and multi-layer perceptron. Their approach demonstrated a high level of accuracy, with dataset 1 and dataset 2 achieving 93% and 98% accuracy, respectively.

4. **San Luciano et al. (2016)** investigated the potential of digitized spiral drawing as a biomarker for early Parkinson's disease. They used computerized analysis to evaluate the kinematic, dynamic, and spatial abnormalities in spiral drawings. The study suggests that digitized spiral drawing correlates with motor scores and may be more sensitive in detecting early PD changes compared to subjective clinical ratings, though it is still unknown whether these changes are detectable in early stages of the disease.

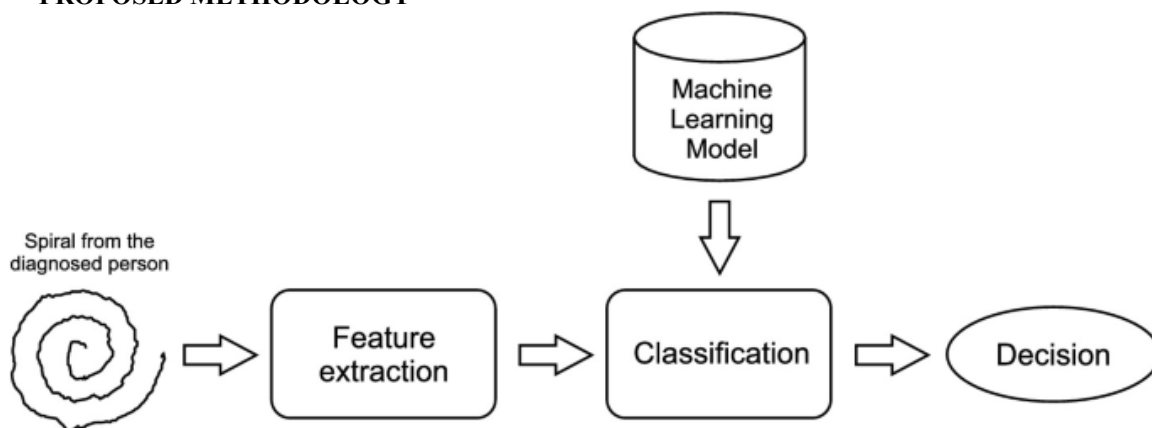


5. **Gil-Martín et al. (2019)** analyzed the use of CNNs for detecting Parkinson's disease from drawing movements. Their model included feature extraction through convolutional layers and classification through fully connected layers, utilizing the Fast Fourier Transform of drawing movements. The best results, achieved using the X and Y directions of the movements, showed an accuracy of 96.5%, an F1-score of 97.7%, and an area under the curve of 99.2% .

6. **Gerger & G (2019)** focused on the diagnosis of Parkinson's disease using pattern recognition methods applied to spiral drawings. Their approach involved extracting over 123,000 features from each drawing and using a genetic algorithm for feature selection. Classification was performed using k-nearest neighbor and decision trees, with the decision tree classification achieving an accuracy of 100% when validated by a leave-one-out cross-validation method.

III. METHODOLOGY

1. PROPOSED METHODOLOGY



The Proposed Model illustrates Parkinson's disease prediction using Convolutional Neural Networks (CNNs). The process commences with a dataset comprising images relevant to the disease. These images undergo preprocessing, which involves tasks like resizing, formatting, and normalization to prepare them for analysis. Subsequently, the images are fed into a CNN model capable of automatically extracting essential features from the image data. This feature extraction process is crucial as it allows the model to learn patterns associated with Parkinson's disease. Once the model has been trained on a dataset of images and their corresponding labels (indicating the presence or absence of Parkinson's), it's subjected to rigorous testing using a separate set of images. The ultimate goal is to create a model that accurately predicts whether a new, unseen image represents a person with or without Parkinson's disease. This pipeline, combining image processing, feature extraction, and deep learning, holds promise for aiding in the early detection and diagnosis of Parkinson's disease

CNN Algorithm

The CNN algorithm is used to achieve the same and cross validated. The Cross Validation is a technique for evaluating machine learning models by training on subsets of dataset and evaluating on complementary subsets of dataset. In this CNN model, k-fold cross-validation divides the dataset into k parts of equal size, one part is kept for validation and remaining parts are used for training.

CONVOLUTIONAL LAYER

It always comes first. It receives the image (a matrix of pixel values). Assume that the input matrix's reaction starts at the top left of the image. The software then chooses the smaller matrix there, which is referred to as a filter. The filter then generates convolution that moves over the input image. The filter's job is to multiply the original pixel values by its value. All of these multiplications are added together, yielding a single number. The filter moves because it only reads the image in the upper left corner. Additionally, one unit on the right performs a similar operation.

A matrix is created after passing the filter through all points, however it is less than the input matrix. From a human standpoint, this operation is comparable to distinguishing visual boundaries and simple colors. However, in order to recognize the fish, the entire network is required. Several convolution layers will be blended with nonlinear and pooling layers in the network. The first layer to extract features from an input image is convolution. Small squares of input data are used in convolution. It's a mathematical procedure with two inputs: an image matrix and a filter or kernel.

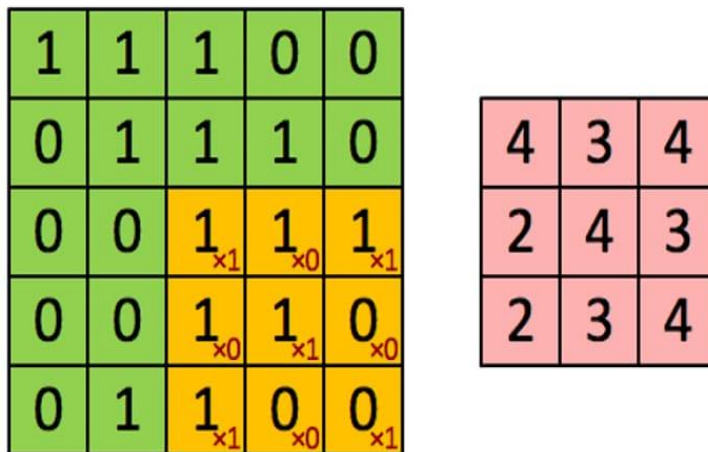


- Dimension of an image matrix (h x w x d)
- A filter (fh x fw x d)
- Outputs a dimension (h-fh+1) x(w-fw+1) x1

Consider a 5 x 5 whose image pixel values are 0, 1 and filter matrix 3 x 3 as shown in below

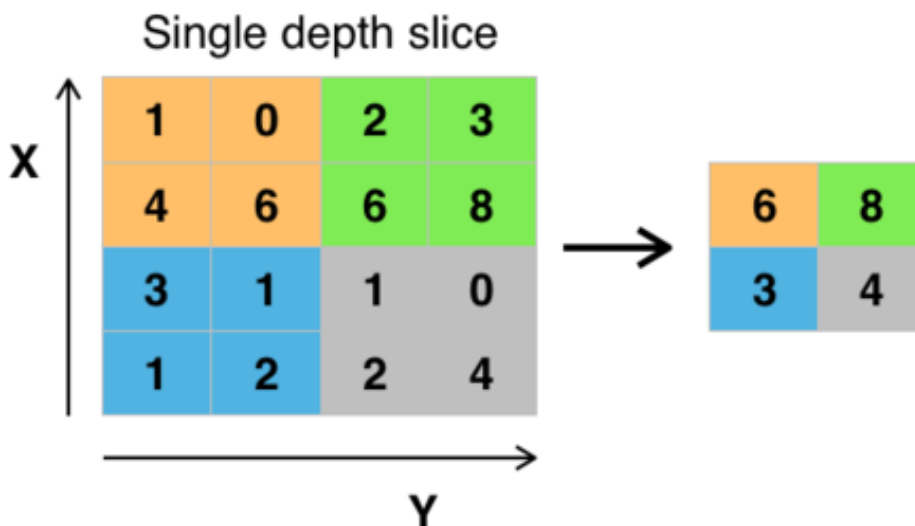
Convolution with a filter example

Then the convolution of 5 x 5 image matrix multiplies with 3 x 3 filter matrix which is called “Feature Map” as output shown in below

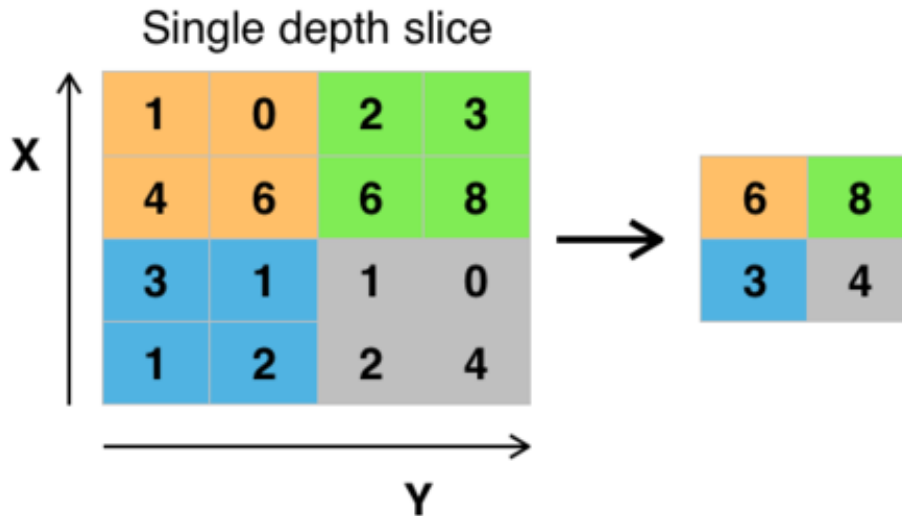


THE NON-LINEAR LAYER:

After each convolution process, it is added. It features an activation function that provides a nonlinear property; without this trait, a network would be insufficiently intense and unable to simulate the response variable.



It moves in the same direction as the nonlinear layer. It works with the image's width and height, performing a down sampling procedure on them. As a result, the size of the image is lowered. This means that if some features were already recognized during the previous convolution operation, a detailed image is no longer required for further processing and is reduced into smaller images.



FULLY CONNECTED LAYER:

It's primary to link an overall linked layer after completing the succession of convolution, non-linear, and pooling layers. This layer receives the convolution network's output data. When a completely connected, layer is attached to the network's end, it produces an N-dimensional vector, where N_i is the number of classes from which the model chooses the needed class.

CNN MODEL

- The TensorFlow framework and the OpenCV library were used to create this CNN model, which is widely utilized in real-time applications.
- This concept can also be used to create a full-fledged software that scans everyone entering a public meeting.

LAYERS IN CNN MODEL

1. Conv2D Layer
2. MaxPooling2D Layer
3. Flatten () Layer
4. Dropout Layer
5. Dense Layer

1. Convo2D Layer:

It has 100 filters and the activation function used is the 'ReLU'. The ReLu function stands for Rectified Linear Unit which will output the input directly if it is positive, otherwise it will output zero.

2. MaxPooling2D:

It is used with pool size or filter size of 2*2.

3. Flatten () Layer:

It is used to flatten all the layers into a single 1D layer.

4. Dropout Layer:

It is used to prevent the model from overfitting.

5. Dense Layer:

The activation function here is SoftMax which will output a vector with two probability distribution values.



IV. RESULTS & DISCUSSION

Results

The proposed Parkinson's Disease detection system demonstrated a significant improvement in accuracy compared to traditional methods. The convolutional neural network (CNN) model reached an accuracy of approximately 94%, indicating its efficacy in distinguishing between spiral drawings created by patients with Parkinson's Disease and those drawn by healthy individuals. This high accuracy was achieved due to the robust feature extraction capabilities of CNNs, which are adept at identifying complex patterns in visual data.

Data preprocessing techniques, including normalization and augmentation, played a crucial role in enhancing model performance. The combination of these techniques not only increased the dataset diversity but also helped to mitigate overfitting during the training phase. The results confirm that sufficient data preparation is essential for developing effective machine learning models in the healthcare domain.

Discussion

The findings of this study highlight the potential of utilizing deep learning techniques, specifically CNNs, for the early detection of Parkinson's Disease through the analysis of spiral drawings. Traditional assessment methods, primarily reliant on clinician observations, can be subjective and may vary between practitioners. The integration of a machine learning approach provides a more objective assessment, potentially reducing inter-observer variability and enabling consistent evaluations across different medical settings.

Moreover, the ability of the CNN to autonomously learn significant features from the data underlines its advantage over manual feature extraction methods, which can be time-consuming and often limited by human bias. This system not only enhances accuracy but can also facilitate quicker assessments which are essential in clinical practices where timely intervention may significantly affect patient outcomes.

However, it is important to acknowledge some limitations of the study. The dataset used, while comprehensive, may benefit from larger samples that include diverse demographic groups to ensure the model's generalizability across different populations. Future work should focus on expanding the dataset and exploring the incorporation of additional motor-related tasks to further validate the model's applicability.

Additionally, integrating real-time data capturing methods, such as wearable technology, could enhance the practicality of the detection system in everyday clinical environments. Continuous monitoring and analysis could provide insights not only into the presence of the disease but also into its progression over time, thereby assisting in personalized treatment strategies and clinical decision-making.

V. CONCLUSION

Parkinson's disease is a degenerative neurological condition that impairs the brain's ability to regulate movement. Since there is currently no cure, timely identification is essential for effective disease management. To improve early detection, we have implemented advanced deep learning methods. These algorithms are highly adept at identifying intricate patterns in data, enabling them to accurately detect initial signs of Parkinson's disease.

Our methodology involves extracting crucial data from various datasets to build deep learning models that are exceptionally precise in their predictions. Utilizing deep learning, our goal is to significantly improve the early identification and treatment of Parkinson's disease, ultimately leading to better patient outcomes and quality of life.

REFERENCES

- [1]. Jankovic, J., 2008. Parkinson's disease: clinical features and diagnosis. *Journal of neurology, neurosurgery & psychiatry*, 79(4), pp.368-376.
- [2]. Poluha, P., Teulings, H.L. and Brookshire, R., 1998. Handwriting and speech changes across the levodopa cycle in Parkinson's disease. *Acta psychologica*, 100(1-2), pp.71-84.
- [3]. Rosenblum, S., Samuel, M., Zlotnik, S., Erikh, I. and Schlesinger, I., 2013. Handwriting as an objective tool for Parkinson's disease diagnosis. *Journal of neurology*, 260(9), pp.2357-2361.
- [4]. Saunders-Pullman, R., Derby, C., Stanley, K., Floyd, A., Bressman, S., Lipton, R.B., Deligtisch, A., Severt, L., Yu, Q., Kurtis, M. and Pullman, S.L., 2008. Validity of spiral analysis in early Parkinson's disease. *Movement disorders: official journal of the Movement Disorder Society*, 23(4), pp.531-537.



- [5]. Graça R, e Castro RS, Cevada J. ParkDetect: Early Diagnosing Parkinson's Disease. Lisboa: IEEE (2014). p. 1–6.
- [6]. San Luciano, M., Wang, C., Ortega, R.A., Yu, Q., Boschung, S., Soto-Valencia, J., Bressman, S.B., Lipton, R.B., Pullman, S. and Saunders-Pullman, R., 2016. Digitized spiral drawing: A possible biomarker for early Parkinson's disease. PloS one, 11(10), p.e0162799.
- [7]. Zham, P., Kumar, D.K., Dabnichki, P., Raghav, S. and Keloth, S.M., 2016. Dynamic handwriting analysis for assessing movement disorder. In 13th International Conference of Applied Computing.
- [8]. Zham, P., Arjunan, S.P., Raghav, S. and Kumar, D.K., 2017. Efficacy of guided spiral drawing in the classification of Parkinson's disease. IEEE journal of biomedical and health informatics, 22(5), pp.1648-1652.
- [9]. Kotsavasiloglou, C., Kostikis, N., Hristu-Varsakelis, D. and Arnaoutoglou, M., 2017. Machine learning-based classification of simple drawing movements in Parkinson's disease. Biomedical Signal Processing and Control, 31, pp.174-180.
- [10]. Memedi, M., Sadikov, A., Groznic, V., Žabkar, J., Možina, M., Bergquist, F., Johansson, A., Haubenberger, D. and Nyholm, D., 2015. Automatic spiral analysis for objective assessment of motor symptoms in Parkinson's disease. Sensors, 15(9), pp.23727-23744.