Survey on Computer Vision-based Neurodegenerative Disease Identification Approaches

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Abstract

The objective is to understand what is meant by Neuro-degenerative problems and how doctors try to identify and diagnose these problems in the present day. The most common among all is the Parkinson's disease which is basically a condition where brain cells start shrinking and the person's control over physical movements weakens over time. The best medical test for identification is Magnetic resonance imaging which helps in early detection of the condition. Artificial Intelligence has recently emerged as a highly potential technique to help doctors diagnose this problem early and correctly. Deep learning models have found useful applications in identifying the existence of NDG in a person by monitoring his/her daily usual activities. Some models useful in this approach have also been explained which take voice recordings as the basis input for identification of NDG. Although these models are capable of achieving extra ordinary accuracy of ¿ 98%, they are only limited to classification, and determining the severity of the condition or recommendation of suitable diagnosis is still a major challenge. Thus the future scope of development and potential obstacles has also been discussed.

1 Introduction

1.1 What are Neurodegenerative problems

Neurodegeneration (NDG) is a medical condition in which the neuron cells in the central nervous system of a human brain stop functioning or die. The condition generally worsens over time as the degeneration process of the neurons accelerates with a person's age, eventually leading to some severe medical disorders, which appear to be physical but the underlying causes are due to mental dysfunctions. Some known diseases following such conditions are Alzheimer's Disease in which the brain shrinks, causing the neurons to die. Common symptoms are a decline in memory, thinking and social skills[1]. Another disease is Parkinson's Disease (PD) which is a progressive disorder visible in physical movements having symptoms such as tremors, stiffness, slowing down of movements and slower reactions. A third kind of condition is Lewy Body Dementia where the mental abilities decline gradually, leading to a disturbance in alertness and attention, and frequent hallucinations. There is no deterministic treatment or proven diagnosis for such diseases yet, but early detection can help slow down the degeneration process and delay adverse effects. In some cases, the prevention from further deterioration of the conditions can also be achieved[8].

1.2 How doctors detect and treat NDG disorders

The degeneration of the cells can be tested in many biological ways. The motive is to detect early signs or visual cues for such conditions. Some early symptoms that can be traced are loss of muscle control, disorientation, emotional blunting, hallucinations, delusion, expressing unwanted feelings and short-term memory loss[21][8]. Other common non-motor symptoms include anhedonia(inability to experience pleasure in usually enjoyable circumstances), loss of smell and taste, mood disturbances, excessive sweating and also prolonged constipation[27]. Among the presently available medical treatments or techniques, **MRI** is considered the best solution for early detection, even before motor symptoms are visible. It helps in recognizing structural changes like atrophy or signal intensity fluctuations[18]. Generally, the diagnosis procedure also includes **positron emission tomography(PET)**, a non-invasive imaging technique to observe the changes in metabolic processes. A conventional method of identifying more than two motor feature symptoms and responsiveness to certain medications is still a famous practice. The use of **Levodopa** is a standard in PD treatment. It suppresses the symptoms of PD

lessening the stiffness, tremor and slowness in individuals. Tremors or involuntary rhythmic movements are the most common movement disorders. **Botulinum toxin** (BoNT) has found its successful applications and positive effects in the treatment of many movement disorders such as restless legs syndrome, spasticity, and most importantly PD. Today it can be seen as a part of the diagnosis for many movement disorders, however, the consistency and universality of its effects are yet to be established[6]. The use of some dopamine agonists is also regular which extends the effect of Levodopa and response in a similar fashion to dopamine as brain cells would normally have. Though generally effective, these present-day treatments have a lot of severe side effects[21].

1.3 Computer Vision

Computer vision(CV) holds a huge potential to detect NDG conditions early. By providing appropriate data, artificial intelligence(AI) models can be prepared to detect a person's condition based on his/her visual symptoms. This area of computer vision, called Human Activity Recognition(HAR) helps in interpreting human motion. Using HAR, one can detect abnormalities in physical movements by comparing different normal behaviours. Data related to gait and other movements can be recorded using smart wearables like watches, shoes and smartphones which have motion sensors built-in to detect movement. Another method is to put multiple motion sensors working synchronously on a person's body and record their movements in a controlled environment. This gives more accurate observations and thus helps the computer implement the AI model better. A third method of CV helpful in PD detection is observing vocal data since a person suffering from PD is bound to experience changes in how he/she speaks or reacts to surrounding sounds. Observing these symptoms using CV is very helpful to detect PD early. Many standard data sets are available to train CV models, some of them are:

1. 195 voice recording instances from 31 people, 23 PD and 8 Healthy Control(HC). The age ranged between 46 and 85 years. An average of 6 samples were recorded per subject using a head-mounted microphone (AKG C420) positioned at 8 cm from the lips[16].

2. voice recording of 188 patients with PD containing 107 men and 81 women. The age ranged between 33 and 87 years. The control group consists of 64 individuals, 23 men and 41 women. Data were collected in accordance with the approval of the Clinical Research Ethics Committee of Bahcesehir University[23].

3. 240 phonetics recordings of 80 persons, 3 recordings each. 40 people were having PD conditions and 40 were HC, all above the age of 50. Speech data collected from the participants was recorded using a portable computer with an external sound card (TASCAM US322) and a headband microphone (AKG 520) with a cardiogram pattern[30].

4. Gaitpdb - Gait features of 73 HC and 93 PD patients. Sixteen sensors, eight on each foot, were integrated into shoes for supervision. The sensor signals collected from each foot channeled the Vertical Reaction Force (VRF), measured in Newton. The assimilated gait data were sampled at 0.01 s time intervals, for an epoch of two minutes, with 3 repetitions of each person[11][20].

5. voice data using mPower application. The app recorded all data collected through interactions with the Bridge Server, a set of web services developed and operated by Sage Bionetworks[4].

6. gait dynamics of patients with Parkinson's disease (n = 15), Huntington's disease (n = 20), amyotrophic lateral sclerosis (n = 13) and 16 healthy control subjects. Stride-to-stride measures of footfall contact times were derived[12].

1.4 Applications of Computer Vision in detecting NDG disorders

Artificial intelligence has gained a significant presence in the healthcare domain, including disease detection, decision support, and the reduction of disparities. AI's central utility is to process logical pieces of information out of the big data fed to it[14]. Combining Machine Learning methods with traditional medical models helps in better recognition of PD. Many diverse AI algorithms and data acquisition methods are useful in the diagnosis of neurodegenerative conditions. Using multivariate vocal data analysis(MVDA) provides better real-time solutions[21]. Many motor(physical) features are looked out for in observing symptoms of PD, such as gait analysis. Other symptoms include hunched posture, fewer facial expressions, and small cramped handwriting.
A key symptom observed for PD is a change in voice. Thus, many attempts are being made to detect the possible onset of PD through voice and speech analysis[5]. Speech disorder is also one of the symptoms where a person stumbles over words, whispers, and falters towards the end of sentences[7]. Table 1 compares various research

Year	Author	Database	Method(Performance)
2011	HK Rouzbahani([22]	23 PD, 8 HC[16]	SVM(91.04%) , KNN(93.83%)
2014	Sharma A.[24]	23 PD, 8 HC[16]	KNN(82%) , MLP(82.35%) , SVM(85.3%)
2016	A Bourouhou[5]	20 PD, 20 HC	Naive Bayes'(65%) , KNN(70%) , SVM(80%)
2018	Marar, S.[17]	23 PD , 8 HC[16]	Random Forest(87.17%), ANN(94.87%)
2019	Yasar A.[30]	40 PD , 40 HC[30]	(ANN) Levenberg-Marquardt(LM) algorithm(94.93%)
2019	Sheibani R[25]	54	Ensemble based method(90.6%)
2020	John M. Tracy[28]	246 PD ,2023 HC	Gradient Boosted Trees(79.7%)
2021	Ouhmida, A.[19]	23 PD , 8 HC[16]	SVM (95.83%), KNN (97.92%), Decision Tree(98.26%)
2023	OURS	23 PD , 8 HC[16]	SVM (97.44%), ANN()

Table 1: Identifying Parkinson's Disease using speech recognition

Year	Author	Sample	Method(Performance)
2015	Ferdous Wahid[29]	23 PD , 26 HC	Random Forest(92.6%)
2016	Shetty S.[26]	64[12]	SVM(83.33%)
2018	Ye, Q. [31]	64[12]	SVM(90.32%)
2018	Klomsae[13]	64[12]	Fuzzy KNN(96.43%)
2019	J. P. Félix [10]	64[12]	SVM(96.8%)
2019	Andrei [2]	93 PD , 73 HC[11]	SVM(100%)
2021	Priya SJ [20]	93 PD, 73 HC[11]	SVM(96.28%)

Table 2: Identification of Parkinson's Disease using gait analysis

attempts made on identifying PD through how a person speaks some phonetics multiple times, or in general the speech patterns.

Another prominent physical symptom of PD is gait analysis. Small, shuffling steps, slowing of movement or complete immobility of the lower body are common symptoms. People experience slowness of movement, posture instability, tremors and rigidity which can be very painful sometimes[26]. Table 2 mentions some of the PD identification models based on gait analysis. Some research has also been done on handwriting patterns for identifying PD as it is observed that people start writing small and crookedly than they used to write during a relatively earlier stage of PD(or before the onset of PD).

2 Proposed Approaches for Identifying PD

2.1 Experimental Setup

The data set as described by Little et al., 2009[16] was selected to perform the experiment. The data set consisted of 195 voice recordings from 31 people, out of which 23 were with the disease and 8 were healthy. There were 19 males and 12 females. The ages ranged between 46 years and 85 years. An average of 6 recordings per person were captured using a microphone fitted at a distance of 8 cm from their mouths. A total of 22 features were extracted which represented attributes of various properties like frequency, amplitude, tonal noise, and frequency variation. The features include:

MDVP: Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)
MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP
MDVP:Shimmer	MDVP:Shimmer(dB)	Shimmer:APQ3	Shimmer:APQ5
MDVP:APQ	Shimmer: DDA	NHR	HNR
RPDE	D2	DFA	spread1
spread2	PPE		

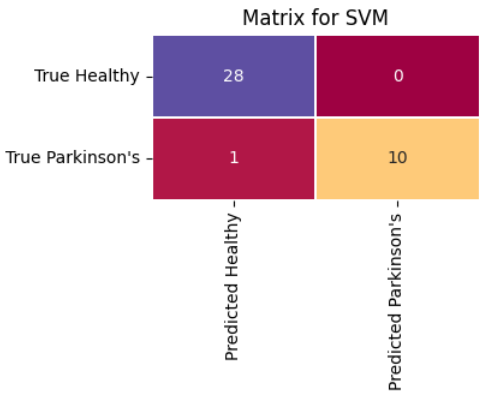

Figure 1: Confusion Matrix for SVM

2.2 Support Vector Machine Approach

First, a conventional method of support vector machine(SVM) was undertaken. An SVM creates a decision boundary for segregating the space into classes and identifies the correct category. The number of features (dimensions in SVM) was reduced from 22 to 8 as some features were simply different representations of the same parameters. This was done using a correlation matrix and some trial and error testing. It was found that the features *MDVP: Fhi(Hz), spread1, MDVP: Fo(Hz), MDVP: Flo(Hz), D2, HNR, and MDVP: Shimmer(dB)* showed maximum relevance in depicting the *status*. The original data was divided into train and test sets in the ratio of 4:1. The training data was then augmented to increase the training set by random oversampling since the number of data points was less for proper training of the model. The SVM model was then trained using the train data and finally tested on the test data which resulted in an accuracy of 97.436%. Fig.1 shows the confusion matrix obtained from testing.

2.3 Artificial Neural Network

A newer approach of ANN was also experimented on the data set for having a robust model for accurate output. The number of features was first reduced to 10 using an auto-encoder, which gave the most relevant parameters for the classification. The data was split into train and test data, and the training data was augmented using over-sampling. Next, a 3-layer dense fully connected neural network model was trained. The experiment can be referred to as given in Fig.2.

3 Current challenges and future scope

Big data, validation, and diagnosis are three critical aspects of establishing a relationship between AI and medicine. The data should not be just recorded during clinical visits but monitored continuously[14]. This creates a challenge for the accuracy of the data, and thus prediction or diagnosis of a disease purely based on AI is not very useful presently[15]. Validating the AI-based results is also challenging, especially in the case of PD, where the symptoms and condition vary greatly according to person and time. To date, AI has only been useful in supplementing the observations of clinical specialists and nothing more. The models are capable enough only to classify as PD or non-PD, not the levels or modifications that happen over time. New attempts are being made to capture data beyond the clinic experience and devise AI algorithms to depict the severity of the patient's condition[9]. The problem of lack of sufficient data can be solved by monitoring continuous movement, voice and response speed through smartphones, wearables and embedded sensors[3]. The detection of molecular subtypes and their mutations will allow for an improved prognosis. According to the current domain knowledge and ongoing research, automation of disease detection using AI is not possible without data on molecular analysis according to the current medical studies. Overall, mechanisms to capture patients' data in a free environment are important for personalizing treatment.

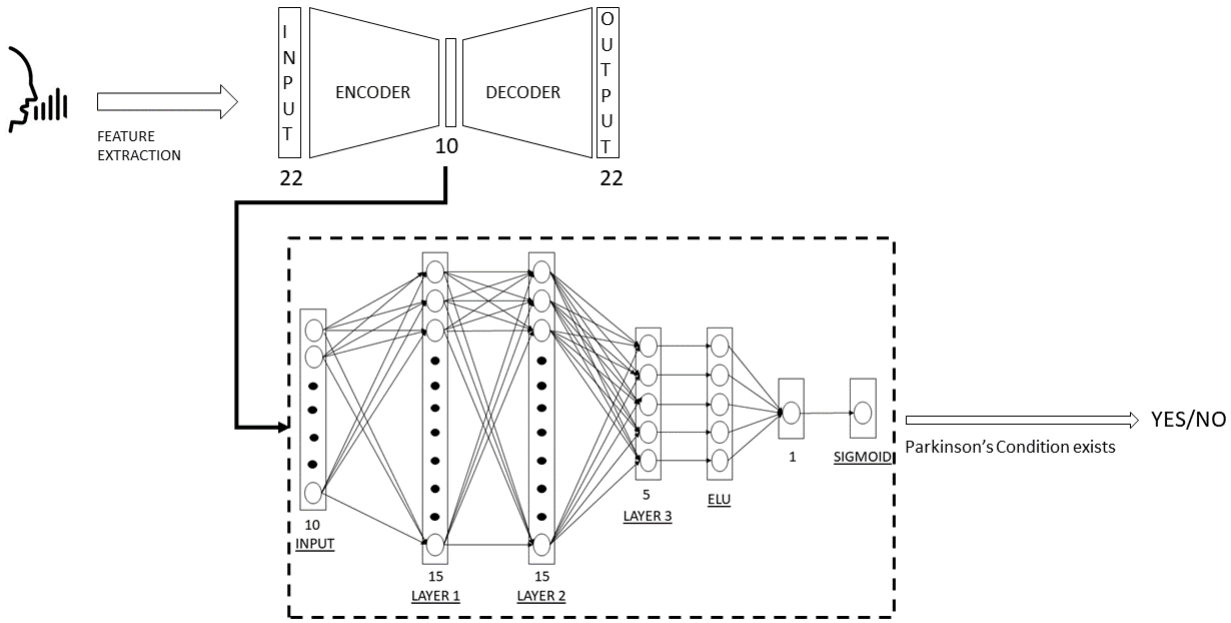

Figure 2: Experimental Model - Fully connected neural network

4 Conclusion

Neurodegeneration is a severe disease to get rid of once occurred. Present-day medical advancements allow for the detection of only certain conditions that too without any robust and standard treatment. AI and ML have immense potential to revolutionize the medical domain. Their use can help doctors to not only detect problems early even up to the smallest detail but also help them to diagnose better, specifically according to the condition. Based on the current research and experiments, some of the techniques like using CNN-based hybrid algorithms on MRI data, including additional modules other than gait in wearables for detecting PD, and developing models which incorporate all, or at least most, of the PD symptoms, instead of focusing on a specific few promise immense potential for rapid advancement in this area.

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