SOFTWARE REQUIREMENT SPECIFICATION

FOR

PREDICTING SEVERITY OF PARKINSON’S DISEASE USING DEEP LEARNING

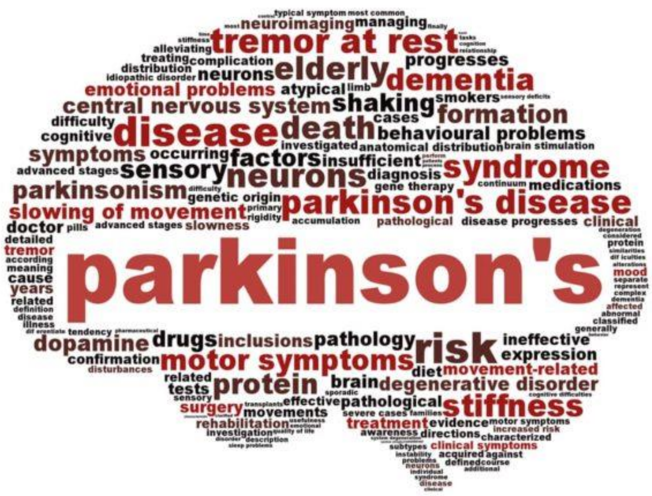

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Table of Contents

1. **INTRODUCTION**

1.1 **PURPOSE**

Parkinson's disease is a neurodegenerative disorder, resulting in progressive degeneration of functions related to motor abilities of the patients due to the damage of dopamine-producing brain cells. The various symptoms of this disease are shaking, difficulty in movement, behavioural problems, dementia and depression. The prime motor symptoms, together, are referred to as "Parkinsonism", or a "Parkinsonian Syndrome". The changes in patients’ voice is one of the common symptoms which can be identified analysing the patients’ voice data. Patient’s voice tends to stutter and progressively becomes affected as the disease becomes more severe. A lot of research has been done to predict Parkinson’s disease in a patient, but less work has been reported to predict its severity.

1.2 **SCOPE**

The scope of our project is recognising the severity of the patients having Parkinson’s disease on the basis of the change observed in their voices during a certain period of time.

1.3 **DEFINITIONS, ACRONYMS, ABBREVATIONS:**

DNN – Deep Neural Network
Deep neural networks use multiple layers of neurons stacked together to create classification and feature selection models.

UPDRS – Unified Parkinson’s Disease Rating Scale
This is a rating scale measurement which indicates whether the patient that has Parkinson’s disease is severe or not based on the values of motor UPDRS and total UPDRS that lies within some certain range.

Total UPDRS – Total Unified Parkinson’s Disease Rating Scale
This is first type of UPDRS scale which provides a higher range of score scale ranging from 0-176.

Motor UPDRS – Motor Unified Parkinson’s Disease Rating Scale
This is the second type of UPDRS scale which measures the motor ability of the patient and based on it generate the value ranges from 0-108.

1.4 **DETAILED PROBLEM DEFINITION**

The proposed methodology for predicting the Parkinson's disease severity using deep learning is outlined in Fig. 1. In first step, the voice data of PD patients is collected for analysis. Then the collected data is normalized using min-max normalization. In the next step deep neural network is designed with input layer, hidden layers and output layer. The number of neurons in the input layer is fixed as the number of attributes in the input data. The output layer contains two neurons corresponds to the two classes – "severe" and "non-severe". The normalized data is fed into the constructed deep neural network for training and testing.

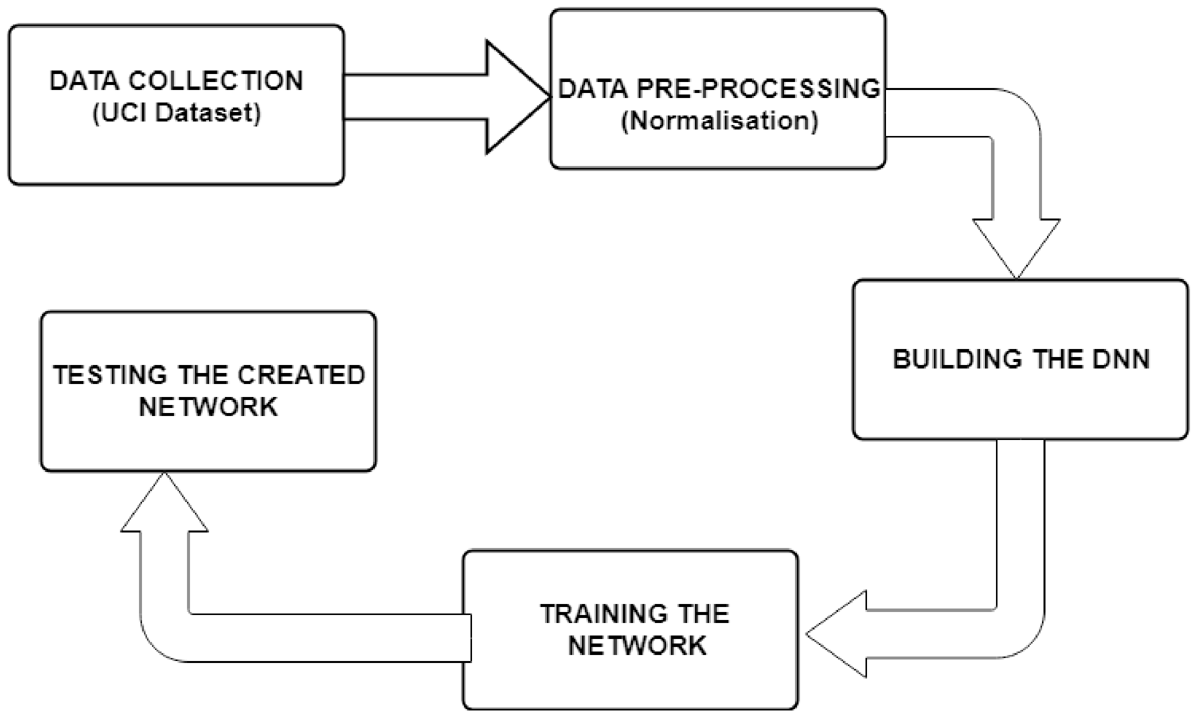

Fig. 1. Proposed deep learning framework

1.4 **REFERENCES**

- Das R. (2010) “A comparison of multiple classification methods for diagnosis of Parkinson disease”. *Expert Systems With Applications*”; **37**:1568-1572.
- Genain N, Huberth M, Vidyashankar R. (2014) “Predicting Parkinson’s Disease Severity from Patient Voice Features.”
- Benmalek E, Elmhamdi J, Jilbab A. (2015) “UPDRS tracking using linear regression and neural network for Parkinson’s disease prediction.” *International Journal Of Emerging Trends & Technology In Computer Science (IJETTCS)*; **4**:189-193.
- Cole B, Roy S, De Luca C, Nawab S. (2014) “Dynamical Learning and Tracking of Tremor and Dyskinesia From Wearable Sensors.” *IEEE Transactions On Neural Systems And Rehabilitation Engineering*; **22**:982-991.
- Angeles P, Tai Y, Pavese N, Wilson S, Vaidyanathan R. (2017) “Automated Assessment of Symptom Severity Changes during Deep Brain Stimulation (DBS) Therapy for Parkinson's Disease.” *International Conference On Rehabilitation Robotics (ICORR)*.
- Galaz Z, Mzourek Z, Mekyska J, Smekal Z, Kiska T, Rektorova I et al. (2016) “Degree of Parkinson's Disease Severity Estimation Based on Speech Signal Processing.” *39th International Conference On Telecommunications And Signal Processing (TSP).*
- Asgari M, Shafran I. (2010) “Extracting Cues from Speech for Predicting Severity of Parkinson's Disease.” *IEEE International Workshop On Machine Learning For Signal Processing.*
- Nilashi M, Ibrahim O, Ahani A. (2016) “Accuracy Improvement for Predicting Parkinson’s Disease Progression”. *Scientific Reports*; **6**. 34181
- Hariharan M, Polat K, Sindhu R. (2014) “A new hybrid intelligent system for accurate detection of Parkinson's disease.” *Computer Methods And Programs In Biomedicine*; **113**:904-913.

2. **THE OVERALL DESCRIPTION**

Data Collection

We have used Parkinson's Telemonitoring Voice Data Set from UCI Machine Learning Repository. The dataset comprises of biomedical voice measurements of 42 patients. The various attributes of the data are subject number, subject age, subject gender, time interval, Motor UPDRS, Total UPDRS and 16 biomedical voice measures. The dataset contains 5,875 voice recordings of these patients. The data is in ASCII CSV format. On an average, there are approximately 200 recordings collected from each patient (identification can be done through the first attribute - subject number).

Data Pre-processing

We have normalized the dataset into a range of 0-1 using min-max normalization. The normalization was done column wise using equation (1): (1)

$$Normalized\ value\ of\ x = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Where x= column value, min(x) = minimum value for that column and max(x) = maximum value for that column

Building the DNN

The total-UPDRS score in the dataset ranges from a minimum value of 5.0377 to a maximum value of 54.992, while it ranges from minimum of 5.0377 to maximum of 39.511 in case of motor-UPDRS scores. We created the train and test datasets by splitting the normalized dataset into parts of 80% (for train dataset) and 20% (for test dataset). Further, separate train and test datasets were created for both motor UPDRS score and total UPDRS score, keeping each of these scores as the output variable in their corresponding files. The normalized values of 16 biomedical voice measures namely Jitter (%), Jitter (Abs), Jitter RAP, PPQ5, DDP, Shimmer(dB), Shimmer: APQ3, APQ5, Shimmer: APQ11, Shimmer DDA, NHR, HNR, RPDE, DFA, PPE are selected as features for classification. The output classes are 'non-severe' and 'severe'. We have defined the range for the various metrics for severe and non-severe classes as shown in Table 1 due to the limitation of values in the dataset.

Table 1. Severity Class range

Metric	Severe	Non-severe
Total-UPDRS	Above 25	0-25
Motor-UPDRS	Above 20	0-20

The algorithm takes in the input dataset and creates an input pipeline, and defines iterators over it, these are variables which helps in scanning over data set. The defined algorithm also provides the functionality to shuffle the dataset in order to provide randomness. After defining the input pipeline, the second step is to feed the input data into the training model, this is done with the help of lambda function. The model after getting data performs training, evaluation and prediction. The training is done by defining arrays of hidden layer with the pre-initialized weights to the layer, which creates and saves model, in the processing system. And in the end, we perform evaluation of the resultant DNN classifier. The DNN Classifier was built using TensorFlow with Keras as the backend. Our neural network contains 16 units in the Input layer, 10, 20, 10 neurons in each of the 3 hidden layers respectively. The network was further trained with 1000 and 2000 steps respectively.

2.1 **EXTERNAL INTERFACE REQUIREMENTS**

2.1.1 **SYSTEM INTERFACES**

Anaconda Spyder: -

Spyder, the Scientific Python Development Environment, is a free integrated development environment (IDE) that is included with Anaconda. It includes editing, interactive testing, debugging and introspection features.

2.1.2 **SOFTWARE INTERFACES**

Python: -

Python is an interpreted, high-level, general-purpose programming language. Created by Guido van Rossum and first released in 1991, Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects.[27]

Python is dynamically typed and garbage-collected. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming. Python is often described as a "batteries included" language due to its comprehensive standard library.

Android Studio: -

Android Studio is the official integrated development environment for Google's Android operating system, built on JetBrains' IntelliJ IDEA software and designed specifically for Android development. It is available for download on Windows, macOS and Linux based operating systems

2.1.3 **HARDWARE INTERFACES**

The proposed model is implemented in a system with Intel Core i5-5200U CPU @2.20GHz and 8 GB RAM.

2.1.4 **COMMUNICATION INTERFACES**

Media Recorder API: -

The Android multimedia framework includes support for capturing and encoding a variety of common audio and video formats. We can use the MediaRecorder APIs if supported by the device hardware.

2.2 **SYSTEM FEATURES**

With the help of these 16 biomedical factors we are analysing the values of Motor UPDRS and Total UPDRS.

Jitter(%)	measures of variation in fundamental frequency
Jitter(Abs)	measures of variation in fundamental frequency
Jitter:RAP	measures of variation in fundamental frequency
Jitter:PPQ5	measures of variation in fundamental frequency
Jitter:DDP	measures of variation in fundamental frequency
Shimmer	measures of variation in amplitude
Shimmer(dB)	measures of variation in amplitude
Shimmer:APQ3	measures of variation in amplitude
Shimmer:APQ5	measures of variation in amplitude
Shimmer:APQ11	measures of variation in amplitude
Shimmer:DDA	measures of variation in amplitude
NHR	measures of ratio of noise to tonal components in the

	voice
HNR	measures of ratio of noise to tonal components in the voice
RPDE	A nonlinear dynamical complexity measure
DFA	Signal fractal scaling exponent
PPE	A nonlinear measure of fundamental frequency variation

3. **SPECIFIC REQUIREMENTS**

3.1 **PERFORMANCE REQUIREMENTS:**

The input dataset is the 16 biomedical voice features and the output variable is Total UPDRS score. The evaluation metrics used in this research are the two UPDRS (Unified Parkinson's Disease Rating Scale) scores - total UPDRS and motor UPDRS scores. The motor UPDRS evaluates the motor ability of the patient on a scale of 0-108, whereas total UPDRS provides a higher range of the score scale ranging from 0-176.

It is also found that the classification based on motor UPDRS score is better than the classification based on total UPDRS score and hence it can be concluded as a better metric for Severity Prediction. Although we have used a dataset of 5875 instances, the accuracy of our approach can be further improved by implementing it on a larger dataset, having more number of instances of each severity class as well as on a combined database of patients' voice data and other patient attributes like gait and handwriting features.

3.2 **SAFETY REQUIREMENTS:**

To make sure the predictions made by the algorithm are not incorrect or invalid the values of input parameters should being the given range after the normalisation.

3.3 **SOFTWARE QUALITY ATTRIBUTES:**

Correctness: The algorithm predicts appropriate values for the complete data set giving high accuracy.

Extensibility: The algorithm trains itself when different data sets are used.

Learnability: DNN keeps updating its training data and keeps improving its accuracy and performance.

Efficiency: DNN with three hidden layers and due to the classification algorithm used the system gives high accuracy and good efficiency.