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DEEP LEARNING METHOD FOR EARLY PROGNOSIS OF PARKINSON'S DISEASE ACUTENESS

Abstract

Generally, Parkinson's disease (PD) in medicine is a long-term neurodegenerative and progressive disorder. In some brain parts, as the dopamine generating neurons die or they are damaged. Then people begin to have difficulty in walking, writing, speaking or making other basic missions. Some of the indications of the disease worsen over time and thus result in increased acuteness of Parkinson's disease. We have proposed a methodology for the prognosis of Parkinson's disease acuteness. In this scientific article, we used deep neural networks in UCI's Parkinson's telemonitoring voice dataset patients. We have utilized Keras and TensorFlow in Python deep learning library to implement our neural network for prognosis the PD acuteness. The correctness values obtained with our method are preferable than the correctness values specified in the previous research test.

Keywords: *parkinson's disease, deep learning, UCI, python, deep neural network, keras, TensoFlow, UPDRS*

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Parkinson xəstəliyinin kəskinliyinin erkən proqnozu üçün dərin öyrənmə metodu

Xülasə

Ümumiyyətlə tibbdə Parkinson xəstəliyi (PD) uzun müddət davam edən neyrodejenerativ və mütərəqqi bir xəstəlikdir. Beynin bəzi hissələrində, dopamin yaradan neyronların öldüyü və ya zədələndikləri üçün insanlar gəzmək, yazmaq, danışmaq və ya digər əsas tapşırıqlar verməkdə çətinlik çəkməyə başlayırlar. Xəstəliyin bəzi əlamətləri zaman keçdikcə pisləşir və beləliklə Parkinson xəstəliyinin kəskinləşməsi ilə nəticələnir. Parkinson xəstəliyinin kəskinliyinin proqnozu üçün metodologiya təklif etdik. Bu elmi məqalədə UCI'nin Parkinson'un telemonitorinq səs məlumatları xəstələrində dərin neyron şəbəkələrindən istifadə etdik. PD kəskinliyini proqnozlaşdırmaq üçün sinir şəbəkəmizi həyata keçirmək üçün Python dərin öyrənmə kitabxanasında Keras və TensorFlow istifadə etdik. Metodumuzla əldə edilən düzgünlük dəyərləri əvvəlki tədqiqat testində göstərilən düzgünlük dəyərlərindən daha üstündür.

Açar sözlər: *parkinson xəstəliyi, dərin öyrənmə, UCI, Python, dərin sinir şəbəkəsi, keras, TensorFlow, UPDRS*

Introduction

In medicine, Parkinson's disease is considered a neurodegenerative disorder. That result in advanced degeneration of functions related to the patient's motor performance due to damage to dopamine generating brain cells. Various symptoms of this disease tremors, movement difficulties, behavioral problems, dementia, depression, etc. The main motor symptoms are referred together to as Parkinson syndrome or Parkinsonism. Changes in the patient's voice are one of the common symptoms that can be identified by analyzing the patient's voice data. The patient's voice tends to stutter and gradually becomes affected as the disease becomes more serious.

In deep learning became a popular method for efficiently analyzing unstructured data, such as speech and audio signals. Deep neural networks use several layers of neurons that are connected together to create a classification, and model selection function. In this article, in-depth training used to analyze a patient's voice data to classify them into "heavy" and "non-heavy" classes. In this work, we have used two UPDRS (Unified Parkinson's Disease Rating Scale) evaluation metrics scores Total UPDRS and Motor UPDRS scores. The Motor UPDRS evaluates the motor capacity of the patient on a scale of 0-108 and the Total UPDRS provides a higher range of the score scale ranging from 0-176.

Related Work

A lot of studies has been done to prognosis Parkinson's disease in patients, but less work has been reported to prognosis its acuteness. In these works, using various methods of machine learning.

In most of the offered research, the features received from speech signals: Galaz Z. et al. (Galaz, Mzourek, Mekyska, Smekal, Kiska, Rektorova, 2016), Asgari M & Shafran I. (Asgari, M, Shafran, 2010) and Tsanas A. et al. (Tsanas, Little, McSharry, Ramig, 2010) used for prognosis the acuteness of PD.

This survey, Angeles P. et al. (Angeles, Tai, Pavese, Wilson, Vaidyanathan, 2017) developed a sensor system for recording kinetic data from the arm in order to assess indications of acuteness changes during Deep Brain Simulation Therapy.

This works, Cole B. et al. (Cole, Roy, Luca, Nawab, 2014: 982-991) explored the used of dynamic machine learning algorithms for detecting the acuteness of tremors and Dyskinesia from the data collected from wearable sensors. In this paper, Das R. et al. (Das, 2010: 1568-1572) on the application of different classification techniques in diagnosing the Parkinson's disease, the neural network was found as the preferable classifier compared to decline and decision tree.

Nilashiet M. et al. (Nilashi, Ibrahim, Ahani, 2016) offered a new hybrid intelligent system using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Regression (SVR) for prognosis the PD progression.

In this works, Benmalek E. et al. (Benmalek, Elmhamdi, Jilbab, 2015: 189-193) used 40-features Dataset and detected nine finest features using Local Learning-Based Feature Selection (LLBFS) to classify PD subjects into four classes (Healthy, Early, Intermediate & Advance), based on their UPDRS score.

Hariharan M. et al. (Hariharan, Polat, Sindhu, 2014: 904-913) offered a hybrid intelligent system using clustering, feature decrease and classification methods for accurate PD diagnosis.

In this research, Li D. et al. (Li, Liu, Hu, 2011: 45-52) proposed a fuzzy-based nonlinear conversion method where PCA used for feature extraction and SVM for PD prognosis.

Chen H. et al. (Chen, Huang, Yu, Xu, Sun, Wang, 2013: 263-271) offered a Parkinson's disease diagnosis system using PCA for feature extraction and Fuzzy KNN for classification.

In this paper, Polat K. (Polat, 2012: 597-609) offered a model using Fuzzy C-Means (FCM) clustering and KNN to diagnosis the Parkinson's disease. Genain N. et al. (Genain, Huberth, Vidyashankar, 2014) used Bagged decision trees to prognosis the PD acuteness from voice recordings of patients and found an improvement of 2% correctness.

In a survey, Åström F & Koker R. (Astrom, Koker, 2011) designed a PD prognosis system using similar feedforward Neural Network and then the output compared against a rule-based system for making the final resolution.

Materials and Method

The offered methodology for prognosis Parkinson's disease acuteness using deep learning shown in Figure 1. In the first stage, the voice data of PD patients collected for experimentation. Then, the data normalized using the min and max normalization. In the next step, a deep neural network established with an input, hidden and output layer. The input layer number of neurons fixed as the number of attributes in the input data. The output layer contains two neurons corresponds to two categories; "seriously" and "not serious". Normalized data fed to the DNN designed for training and testing.

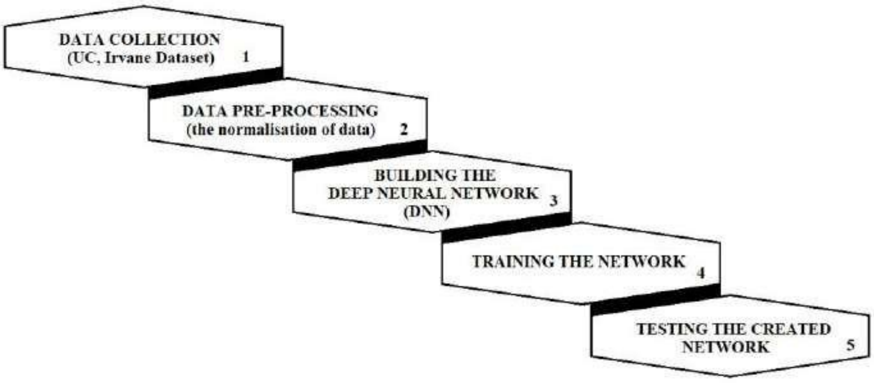


Fig.1. Recommended deep learning framework.

The recommended model implemented in a system with an Intel Core i7-4710 MQ CPU @ 2.50 GHz and 8 GB of RAM. The Python library, Keras (tf.keras) (15) and TensorFlow (tf.estimator) (16) used toimplement the Deep Neural Network.

12.1.Data Collection

Here we have used the Parkinson's telemonitoring voice dataset (Tsanas, Little, McSharry, Ramig, 2010: 884-893) from the UC, Irvine machine-learning repository (16). The data set is comprised of 42 patient's biomedical voice measurement. The different attributes of the data are 16 biomedical voices, the number of subjects, the age of subjects, the gender of subjects, the interval of time, Motor UPDRS, Total UPDRS.

This dataset includes 5,875 voice recordings of the patients. The format of the data is ASCII CSV. On average, there are around 200 recordings composed from every patient (identification can be done through the initial attribute number).

12.2.Data Pre-processing

We have normalized the Dataset in the sequence of 0 to 1 using minimum and maximum normalization. The normalization, are performed on columns using the equation (1).

$$\textbf{Normalized value of x} = \frac{\textbf{x – minimum (x)}}{\textbf{maximum (x) – minimum (x)}} \qquad \textbf{(1)}$$

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

12.3.Building the Deep Neural Network (DNN)

There is a range from a minimum value of 5.0377 to a maximum value of 54.992 in case of Total UPRDS score. The Motor UPDRS score in the dataset ranges from a minimum value of 5.0377 to a maximum value of 39.551. We composed the training datasets and testing dataset by splitting the normalized dataset into parts, for the training datasets of 80% and for the testing datasets 20%. In addition, separate training datasets and test datasets were composed for both Motor UPDRS score and Total UPDRS score. We kept each of these scores as the output variable in their corresponding files.

The normalized values of 16 biomedical voice measures are selected as features for classification as indicated in Table 1.

Jitter%, JitterAbs, Jitter:RAP, Jitter:PPQ5, Jitter:DDP	Several measures of variation in fundamental frequency
Shimmer Shimmer(dB) Shimmer:APQ3 Shimmer:APQ5 Shimmer:APQ11 DDA	Several measures of variation in amplitude
NHR HNR	Two 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

Table 1. Biomedical Voice Features.

The output classes are two categories: "seriously" and "not serious". We have outlined the range for the various metrics for seriously and not serious classes as indicated in Table-2 necessary to the restriction of values in the dataset.

Metric	Total-UPDRS	Motor-UPDRS
Seriously	Above 25	Above 20
Not Serious	0-25	0-20

Table 2. Acuteness Class Range.

The algorithm, get in the input dataset and compose an input pipeline, and describes iterators over it. These ones are variables whichever help in scanning over the Dataset. The described algorithm also provides the functionality to confuse the dataset in order to provide randomness. After describing the input pipeline, with the help lambda function, the second step is to feed the input data inside the training model. The model after obtaining data performs training, evaluation, and prognosis. The training is done by describing the order of the hidden layer with the pre-initialized weightiness to the layer, whichever creates and saves model, in the processing system. Finally, we will perform an evaluation of the resulting DNN classifier. The DNN classifier designed using as the backend TensorFlow with Keras. Our neural network including 16 units in the Input layers, in order of 10, 20, 10 neurons in each of the three hidden layers respectively. The network furthermore trained with 1000 and2000 steps seriatim.

Research result

There is 16 biomedical voice attributes input dataset and the output changeable is Total UPDRS score. Theclassification correctness obtained is 94.4422% and 62.7335% for training and testing dataset seriatim.

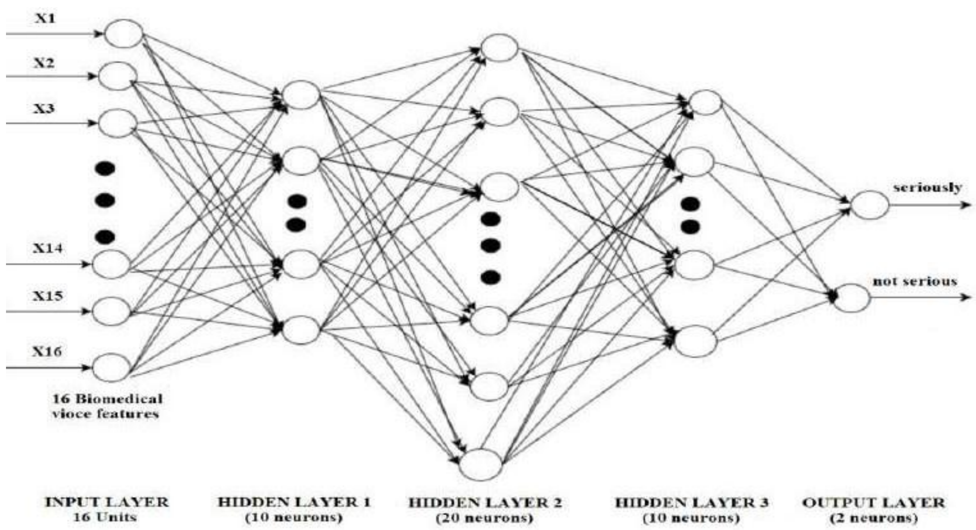
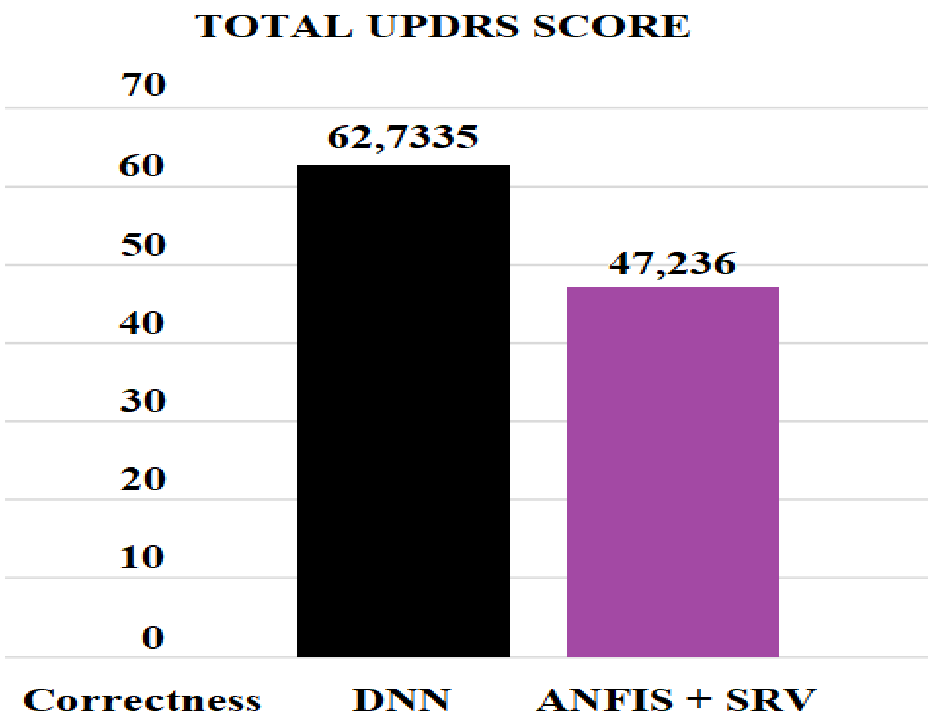


Fig.2. Recommended Deep Neural Network.



3.1. First experimentation is Parkinson's disease acuteness prognosis on the basis of Total UPDRS Score.

We compared our experiment with that of the research work by Nilashi M. et al. (Nilashi, Ibrahim, Ahani, 2016) since they appraised their model on the same UC, Irvine Parkinson’s Telemonitoring Voice Dataset. They used ANFIS and SVR toprognosis Parkinson's disease progression. Their research produced mean correctness of 47.2% for the Total UPDRS score. The performance collection of classifiers for Total UPDRS score is indicated in Fig.3.

3.2. Second experimentation is Parkinson's disease acuteness prognosis on
3.3. the basis of Motor UPDRS Score.

In this experiment, the input dataset is the 16 biomedical voice attributes and the output changeable is Motor UPDRS score. The classification correctness obtained is 83.367% and 81.6667% for training and testing dataset seriatim. In the collection of this, the methodology recommends by Nilashi M. et al. (Nilashi, Ibrahim, Ahani, 2016) produced average correctness of 44.3% for the Motor UPDRS score. The performance collection of classifiers for Motor UPDRS score is indicated in Fig.4.

Fig.3. Correctness Comparing for Total UPDRS score.

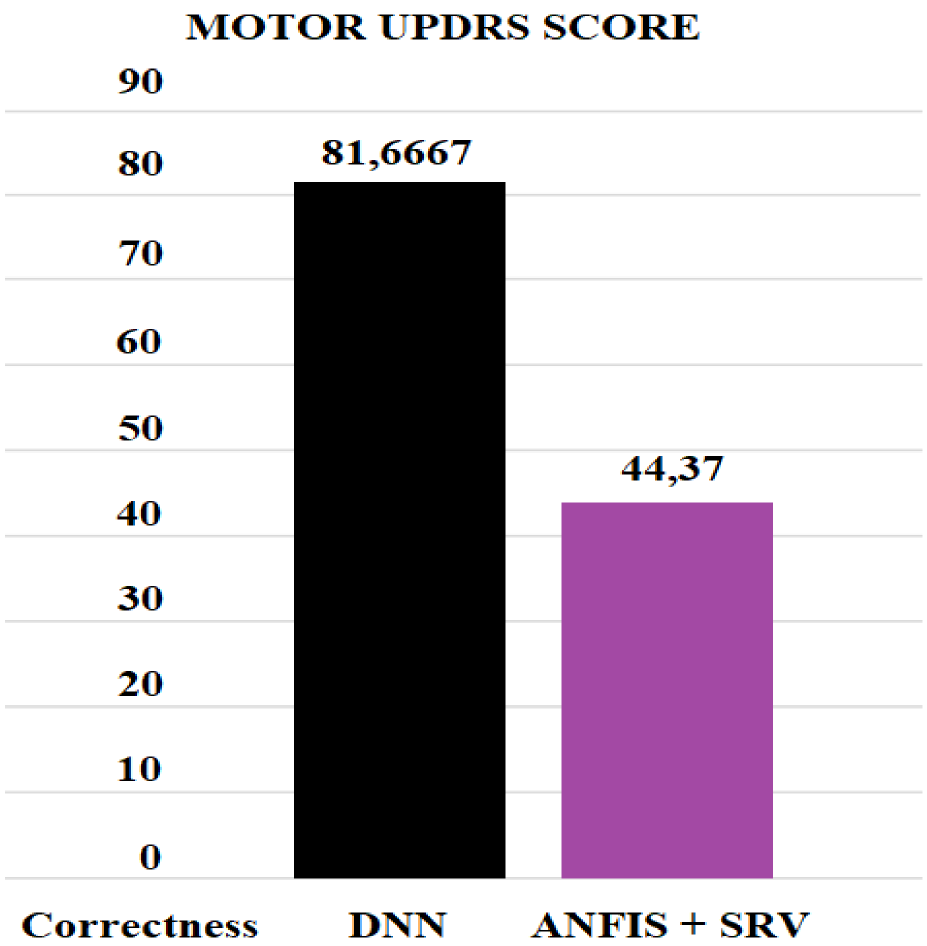


Fig.4. Correctness Comparing for Motor UPDRS score.

Conclusion

In this work, we have implemented a deep neural network to prognosis the acuteness of Parkinson's disease. The recommended DNN model achieved better correctness compared to other existing methods. It is also found that the categorization based on the Motor UPDRS score is finest than the categorization based onthe Total UPDRS score. Therefore, it is able to conclude as the finest metric for acuteness prognosis. We have used a dataset of 5875 instances, but the correctness of our approach can be further advanced by implementing it on a big dataset. Having more number of instances of each acuteness class as well as on a unified database of patients voice data and other patient attributes: like walking and handwriting features.

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