# Predicting UPDRS Scores in Parkinson's Disease Based on Deep Learning

Yinan Li

College Of Medical Information Engineering, Guangdong Pharmaceutical University, GuangDong, 510006, China

1900507119@gdpu.edu.cn

**Abstract.** Parkinson's disease is a progressive neurological disorder that has a significant impact on the quality of life of millions worldwide. Despite well-defined symptoms and known pathophysiological mechanisms, early diagnosis and effective treatment of Parkinson's disease remain considerable challenges. At the same time, due to life pressure and unhealthy lifestyle, Parkinson's and other diseases of the elderly have a trend of earlier onset. This study employed deep learning techniques to predict Unified Parkinson's Disease Rating Scale (UPDRS) scores in Parkinson's patients and investigated the relationships between various disease symptoms, offering insights into early prevention and intervention strategies. The research utilized the Parkinsons telemonitoring dataset sourced from the University of California, Irvine Machine Learning Repository, featuring data from 42 individuals with Parkinson's disease. Motion characteristics and demographic factors, including age and gender, were analyzed to determine the feasibility of computational models in assessing UPDRS scores among Parkinson's patients. Four distinct models including XGBRegressor, DecisionTreeRegressor, LinearRegression, and KNeighborsRegressor were employed, where XGBRegressor and DecisionTreeRegressor demonstrated superior performance across the three evaluation metrics. The proposed model offered the potential for early identification of disease severity in Parkinson's patients, thereby facilitating the development of more precise treatment strategies. This research represented a significant step towards addressing the diagnostic and treatment challenges associated with Parkinson's disease, ultimately aiming to enhance the overall quality of life for those affected by this debilitating condition.

**Keywords:** Parkinson's Disease, UPDRS Scores, Deep learning, Machine learning

## 1 Introduction

Neurological diseases are the leading cause of disabling diseases worldwide, and Parkinson's disease is the fastest growing neurological disease in the world [1]. Parkinson's disease (PD) caused by viral infection is not rare and transmission of



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severe acute respiratory syndrome coronavirus (SARS-CoV-2) [2]. So, it's suspected that the COVID-19 epidemic could contribute to the Parkinson's disease epidemic [3]. In addition, unhealthy lifestyle can affect the onset or course of Parkinson's disease, such as taking caffeine, nicotine and alcohol [4]. Young-onset Parkinson's disease is not uncommon, and it is important to correctly diagnose the specific cause and provide appropriate counseling, family and work plans, and the choice of appropriate treatment [5]. Moreover, many other mental disorders have similar symptoms to Parkinson's disease and can easily be confused when diagnosed [6].

According to data from the Global Burden of Disease Study and the Institute for Health Metrics and Evaluation, the prevalence of Parkinson's disease has been steadily increasing from 3.3 million people in 1990 to 8.5 million people in 2019 [7]. This trend underscores the urgent need for more effective methods of diagnosis and treatment for Parkinson's disease. Additionally, the assessment of the disease's onset and severity plays a crucial role in its diagnosis and treatment. Typical symptoms of Parkinson's disease include hand tremors, muscle rigidity, bradykinesia, and balance issues, all of which can significantly interfere with daily life and motor function. Moreover, the presence and specific manifestations of these features can be used to distinguish Parkinson's disease related to Parkinson's disease [8]. There is evidence that a number of life conditions, including constipation, urinary and sexual dysfunction, and the recent decline in cardiac chronotropic response to exercise, may be part of the preParkinson phenotype and can be used as predictive biomarkers [9].

The Unified Parkinson's Disease Rating Scale (UPDRS) is a clinical tool used to assess the severity of Parkinson's disease and the manifestation of symptoms in patients. Initially introduced by Parkinson's disease researchers in 1987, it has undergone multiple revisions and improvements to become widely accepted as a standard for evaluating Parkinson's disease [10]. Typically administered by physicians or trained healthcare professionals, the UPDRS helps in determining the condition of the patient and devising individualized treatment plans. UPDRS scores are typically conducted at different treatment time points to monitor disease progression and treatment effectiveness. UPDRS is valuable for assisting physicians in treatment planning, tracking disease progression, and assessing the effectiveness of various treatment approaches. However, the unified assessment scale used for the progression of Parkinson's symptoms not only requires patients to go to the clinic to complete time-consuming physical examination, but also needs to pay a high cost, so it is a time-consuming and laborious assessment method for both patients and clinical medical staff [11]. Machine learning is a statistical method based on computer technology, which can train data sets and find common patterns from a large amount of data. The method of machine learning can help clinicians to classify different types of patients [12]. Various models of machine learning are suitable for various health registries and large groups of individuals identified by biobanks to be monitored for simple and rapid testing [13]. Computer vision is an attractive, contactless, potential automated assessment solution for Parkinson's disease, made possible by recent advances in computing power and deep learning algorithms [14]. In addition, it is feasible to realize automatic management of advanced Parkinson's patients with artificial intelligence (AI)-based technology, which can not only improve the quality of care, but also reduce the cost of patients and healthcare system, which is very advantageous [15]. In recent years, deep learning techniques have gained widespread attention in the field of medicine. Deep learning, known for its exceptional ability to handle complex data and extract high-level features, is considered a potential tool for improving the diagnosis and treatment of Parkinson's disease. Long Short-Term Memory (LSTM) has achieved good results in the prediction of Alzheimer's disease, which is also a neurodegenerative disease, therefore, the LSTM is applied in the present study.

This research explored the potential of deep learning in the diagnosis and treatment of Parkinson's disease and its ability to enhance patient management and predict disease progression. Taking into account the characteristics of Parkinson's disease, the data set used in this study included the total UPDRS score and the motor UPDRS score for a more comprehensive and effective assessment of the patient's condition.

# 2 Methods

## 2.1 Data Source and Composition

The dataset used in this study is sourced from the University of California, Irvine Machine Learning Repository, a widely-used repository in the fields of machine learning and data science. The dataset comprises a series of biomedical voice measurements from 42 early-stage Parkinson's disease patients. These patients were part of a six-month trial aimed at remote monitoring of symptom progression. The initial voice recordings were automatically captured at the patients' homes and subsequently processed into digital data. The columns of the dataset have a total of 5875 recording samples including subject ID, subject age, subject gender, test time, motor UPDRS score, total UPDRS score, and 16 biomedical voice measurement data. Among the study subjects, 28 out of 42 are male, and the rest are female. The age of the study group ranges from 36 to 85 years, with an average age of 64.4 and a median age of 65 years. To address the issue of varying data lengths among different subjects, missing data is imputed with zeros.

## 2.2 Data Correlation Analysis and Feature Selection

In this study, a correlation analysis between age, gender, and other feature data in the dataset was conducted (Fig.1). Age, gender, and time of the test had relatively low correlations with the other data, while the individual audio data had relatively high correlations with the other data. Within the audio data can be roughly divided into Jitter, Shimmer, and other (such harmonicity-to-noise ratio (HNR), etc.) three parts. (Fig.2)

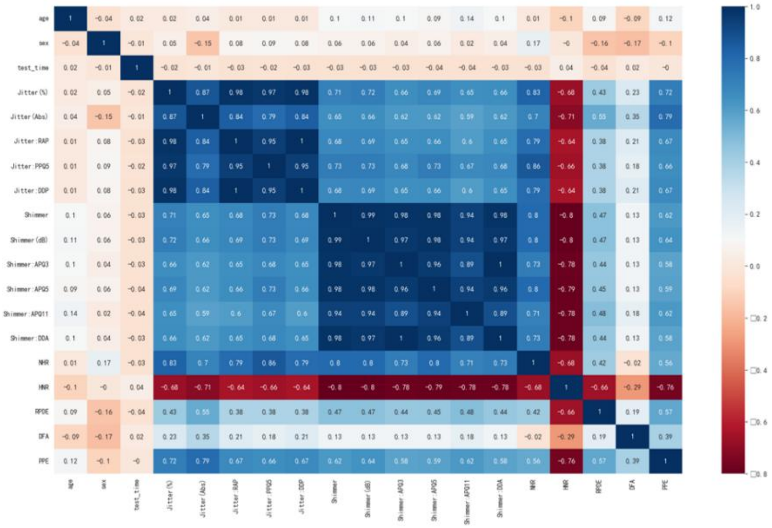


**Fig. 1.** Heatmap of the correlation between each index.

(Photo/Picture credit: Original)

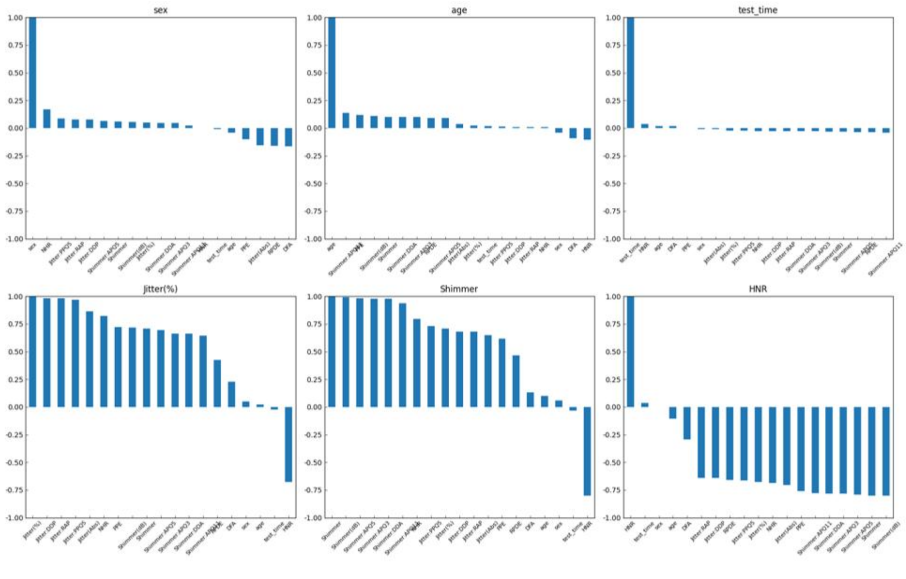


**Fig. 2.** Correlation between sex, age, test_time, Jitter(%), Shimmer, HNR and other indicators.

(Photo/Picture credit: Original)

### 2.3 Traditional Models

Four traditional machine learning models widely used in the field of machine learning (XGBRegressor, DecisionTreeRegressor, LinearRegression, and KNeighborsRegressor) were chosen. Each element in the neural network may be an element that leads to eventual Parkinson's disease, and time - and site-dependent dysfunction in this neural network may be the general basis for the emergence of psychosis, not only in Parkinson's disease and schizophrenia spectrum disorders, but also in other neuropsychiatric disorders, psychosis and sometimes movement disorders may be encountered [16]. These models were selected for comparison. This helped determine which type of model performs best at solving a particular problem.

### 2.4 Deep Learning Models

In this study, a neural network model primarily based on Long Short-Term Memory was constructed (Fig.3). LSTM networks, with their gate functions, had revolutionized deep learning, excelling in capturing long-term dependencies in sequential data, and they are the focal point of research and applications in the field [17]. This model included an input layer, two hidden layers, and two output layers. The sigmoid activation function was chosen to capture nonlinear features. The core model structure employed LSTM and a model used for processing time-series data. The loss function used in the experiments was a combination of Root Mean Squared Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - y_i)^2} \tag{1}$$

and Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{m} \sum_{i=1}^{m} |y_i - y_i| \tag{2}$$

designed to enhance the model's versatility:

$$\mathrm{Loss} = (1 - \alpha)\mathrm{MAE} + \alpha\mathrm{RMSE}(0 \ll \alpha \ll 1) \tag{3}$$

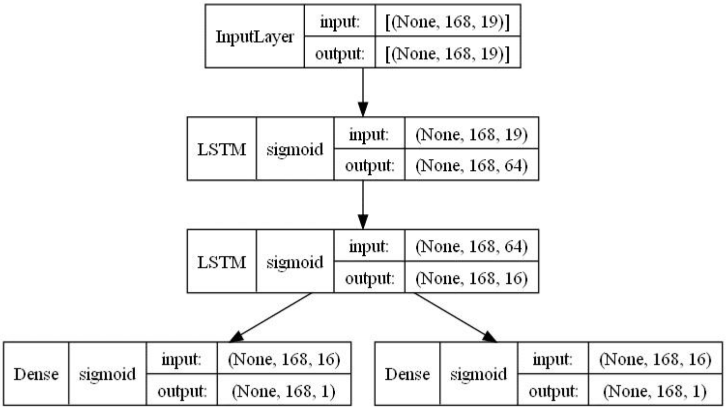


**Fig. 3.** The LSTM model constructed in this experiment.

(Photo/Picture credit: Original)

LSTM model with varying alpha values were trained, all for 1000 iterations, using a learning rate of 0.0001. Among these models, those with alpha values of 0 and 0.5 showed relatively better decreases in loss function values, which were also reflected in the final evaluation metrics.

For the constructed neural network model, the model's performance with different alpha values for the loss function were tested. It was observed that the actual performance of the models varied with different alpha values.

### 2.5 Evaluation metrics

R2 (a higher R-squared value suggests that the model better explains the data variation, and a value closer to 1 indicates a better model fit), MAE, and Mean Squared Error (MSE) were used as evaluation metrics to comprehensively assess these five models [18]. R2, MAE, and MSE were utilized as evaluation metrics to comprehensively assess these five models, offering a multifaceted assessment framework that considers both explanatory power, absolute error, and variance in predictions.

## 3 Results

Through the analysis of a correlation heatmap, the highest positive correlation between age and gender with the Shimmer. Through further analysis of the heatmap, it was founded that age, gender, test time, and audio data had relatively low correlations with each other, while there were higher correlations among the various audio data. Therefore, this study primarily focuses on the correlation analysis among different audio data, including jitter, shimmer, and HNR acoustic parameters.

By analyzing the dataset's correlations, age, gender, test time, and audio data were considered relatively important features. Among the audio data, features such as jitter and shimmer demonstrated higher importance.

By the three different evaluation metrics, on the R2 index, both the XGBRegressor and DecisionTreeRegression models were greater than 0.95. The MAE and MSE of these two models were also the lowest among all models. KNeighborsRegressor also had good results with R2, with regressor of about 0.70. The MAE and MSE for KNeighborsRegressor were also relatively low, all the R2 scores of this model beyond the 0.95, it is obviously that this model had the best performance (Fig. 4). However, considering the significant internal variability in the dataset, this model may carry a higher risk of overfitting. Conversely, LinearRegression performed the worst. In this study, KNeighborsRegressor demonstrated relatively moderate performance, which may be attributed to the dataset's size. For different alpha values, the LSTM model presented an effect between the traditional model KNeighborsRegressor and LinearRegression. Among them, whether on the indicators MAE and MSE or R2, the best effect was achieved when the alpha value is 0.5 (Fig.4).

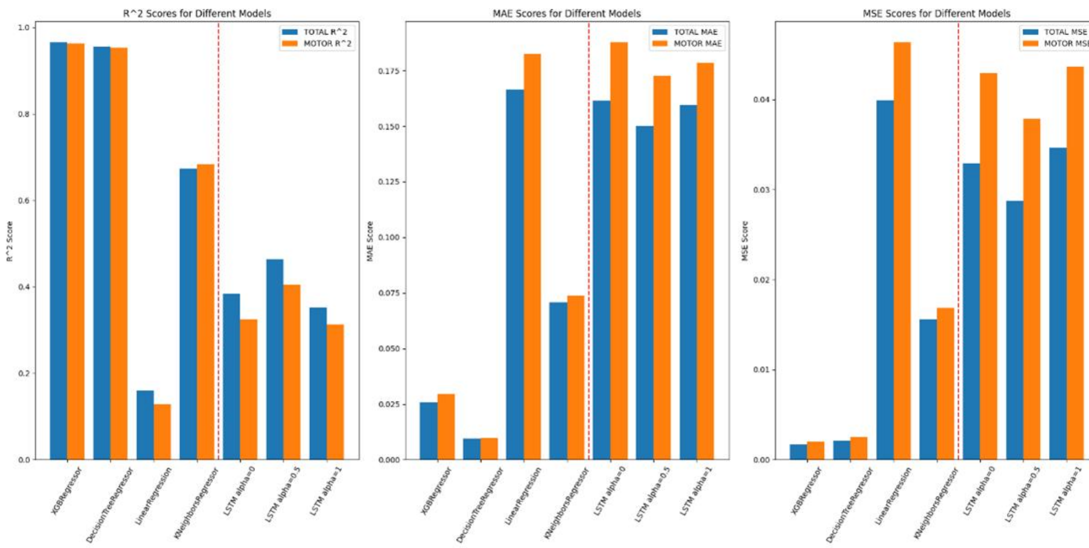


**Fig. 4.** The R2, MAE, and MSE results of each model.

(Photo/Picture credit: Original)

## 4 Discussion

This research evaluated several machine learning models, including XGBRegressor, DecisionTreeRegressor, LinearRegression, KNeighborsRegressor, and a deep learning model based on LSTM in Parkinson's disease diagnosis. XGBRegressor performed the best in predicting UPDRS scores, with R2 scores exceeding 0.95. It is worth noting that the XGBoost model has shown good results in the processing of various medical data, and this study also proves the excellent effect of XGBoost in the processing of Parkinson's disease data [19-21].

This study included a deep learning model, primarily based on LSTM, highlighting the potential of deep learning techniques in Parkinson's disease research. Deep learning has shown promise in handling complex data, and the LSTM-based model provided competitive results. The advantages of the LSTM model include its flexibility, adaptability to various alpha values, effective capture of long-term dependencies, suitability for large-scale datasets, low data preprocessing requirements, capability to handle non-stationary time series, and applicability to multivariate time series, making it a powerful choice for time series modeling and forecasting in diverse fields. Further exploration of deep learning architectures and larger datasets may improve the predictive accuracy and generalizability of these models. It excels in handling multimodal data fusion, automatically learning relevant features, and real-time monitoring, making it particularly well-suited for capturing subtle early-stage disease signs that may be challenging for traditional techniques. Additionally, deep learning enables personalized diagnoses, can handle large-scale medical datasets, and streamlines the diagnostic process through automation. However, it also necessitates large datasets, addresses data privacy concerns, and requires solutions for model interpretability. When used in conjunction with conventional medical assessment methods, deep learning has the potential so significantly enhance the accuracy and reliability of early Parkinson's disease diagnosis.

The correlation analysis revealed that age, gender, test time, and audio data were important features for predicting UPDRS scores. Among the audio data features, jitter and shimmer were of higher importance. These findings emphasize the importance of considering a variety of demographic and voice-related features when developing Parkinson's disease prediction models. It should be acknowledged that the dataset used in this study had some limitations. The relatively small sample size can affect the models' generalizability. It must be noted that the limited sample size of the dataset restricts the models' performance, especially considering the dataset's significant internal variations and the potential risk of overfitting. Additionally, the dataset has varying data lengths among subjects, necessitating data imputation, which may introduce potential bias. Future Parkinson's disease associated research may focus on larger, more diverse datasets, advanced feature engineering, and longitudinal data to enhance prediction and management. Additionally, exploring clinical applications and improving model interpretability is essential. Ethical considerations, including patient privacy, must be prioritized in studies involving patient data. As with any medical research, future studies involving patient data should carefully consider ethical issues such as patient privacy and informed consent [22-25].

## 5 Conclusion

This study demonstrated the potential of both traditional machine learning models and deep learning techniques in predicting UPDRS scores in Parkinson's disease. Further research with larger datasets and a focus on clinical applications is needed to advance the field and improve the diagnosis and management of Parkinson's disease.

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